THREE ESSAYS ON CLIMATE CHANGE, RENEWABLE ENERGY AND AGRICULTURE IN THE US

A Dissertation

by

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ABSTRACT

This dissertation contains three essays. The first essay addresses climate impacts on agricultural yields. One practical difficulty in estimating climate impacts is the presence of regionally correlated but omitted factors such as solar radiation and wind speed. Typical panel estimations account for time invariant omitted variables, but do not handle time varying ones that are regionally correlated. To overcome this, an estimation approach incorporating spatial structure is used. We find that the resultant estimates exhibit improved out-of-sample prediction accuracy compared with conventional panel model results but still reveal basic findings found elsewhere in the literature on relationships between temperature and crop yield.

The second essay is about projection of biofuel production and practical considerations involving expensive biorefineries. Many analyses addressing national level expanded biofuel production exhibit unrealistic, time varying locations of facilities. Namely, once built biorefineries are fixed in location, technology and general class of feedstocks they use but these studies ignore such facts. To examine the implications, we do a market penetration analysis with and without that fixity. We find that neglecting asset fixity leads to upwardly biased projections of ethanol attractiveness, as well as unrealistic production variations over time and space. In particular, when asset fixity is considered the price needed to achieve cellulosic market penetration levels comparable to those in legislation is significantly increased, reaching \$1.06/liter as opposed to \$0.79/liter without it.

The third essay examines renewable electricity and its future market share. Investments in renewable electricity have increased recently due to rapid technological progress. Questions going forward are: (1) Will such technical achievement stimulating market based adoption persist? (2) Are additional developments needed to enhance additional adoption? These questions are addressed in this study using a sector modeling approach. The results indicate that adoption of renewable electricity under current projections of technical progress, will lead to a 25% market share by 2050. If greater market shares are desired, we find this can be stimulated by faster technological progress, reliability enhancing electricity storage and power system management, or direct carbon pricing, with combinations of these supporting as much as a 60% market share by 2050.

DEDICATION

To my dear family

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All work for the dissertation was completed by the student with collaboration. Specifically, the first essay is coauthored with Bruce A. McCarl and Ximing Wu from Department of Agricultural Economics, Texas A&M University. Both Drs. McCarl and Wu contributed to analysis design and writing. All modeling was conceptualized and implemented by Zidong Wang plus all initial writing. All three authors contributed to the document redraft. the second essay is coauthored with Bruce A. McCarl, Department of Agricultural Economics, Texas A&M University and Marta Wlodarz, McKinsey & Company, Inc. Switzerland. Bruce McCarl suggested the consideration of asset fixity and contributed throughout. Marta Wlodarz did an initial examination of the study and an initial model. Zidong Wang re-specified the model and did all of the analysis herein plus constructed the initial draft and led the document redrafting process. The third essay is coauthored with Bruce McCarl, Department of Agricultural Economics, Texas A&M University and Stephen Polasky, Department of Applied Economics, University of Minnesota. Both Drs. McCarl and Polasky contributed to model specification, analysis design and writing. All modeling was conceptualized and implemented by Zidong Wang plus all initial writing. All authors contributed to the document redraft.

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NOMENCLATURE

AEO	Annual Energy Outlook
AF	Asset Fixity
ATB	Annual Technology Baseline
CO_2e	CO_2 equivalent
DDay	Degree Day
EIA	Energy Information Administration
EISA	Energy Independence and Security Act
EPA	Environmental Protection Agency
FASOM	Forestry and Agricultural Sector Optimization Model
GHG	Greenhouse Gas
GW	Gigawatts
ITC	Investment Tax Credit
IPCC AR5 WG3	Intergovernmental Panel on Climate Change Annual Report 5 Working Group 3
KWh	Kilowatt-hour
LCA	Life-cycle Assessment
MT	Metric Ton
MWh	Megawatthour
NREL	National Renewable Energy Laboratory
ReEDS	Regional Electricity Deployment Model
RFS2	Renewable Fuel Standard

RMSE	Root Mean Squared Errors
SDM	Spatial Durbin Model
SEM	Spatial Error Model
OLS	Ordinary Least Squares
PTC	Production Tax Credit
PV	Photovoltaic

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CHAPTER I

INTRODUCTION

Food security, affordable and clean energy and actions to combat climate change and its impact are among the top goals of the United Nations sustainable development initiative (United Nations 2015). Progress towards achieving these goals can be made via efforts and increased understanding in three interlinked areas, namely climate change mitigation, renewable energy and agricultural vulnerability and production.

Changes in climate impact human and natural systems in multiple ways. The vast majority of crop production, for example, is directly influenced by current weather conditions such as precipitation and temperature, and is thus vulnerable to climate changes (Adams et al. 1990). Assessing climate change impacts on agriculture helps shape policy for food security and provides information on needs for adaptation and mitigation investment. On the other hand, agriculture and rural area can help reduce the major driver of climate change – greenhouse gas emissions by providing feedstocks or lands for renewable biomass based, wind and solar energy production.

On the feedstock side the agriculture sector is currently providing about 365 million dry tons for energy generation. This biomass is now used as a feedstock for: a) ethanol and biodiesel production replacing petroleum in transportation fuel and b) generating electricity using biomass as an energy source. In the US, annual ethanol production is around 57 billion liters (15 billion gallons), slightly over 10% of the total gasoline consumption in 2016 (US EIA 2017d) and there is talk of substantial increases. For example the goals in the Renewable Fuel Standard (RFS2) within the Energy

Independence and Security Act (US Congress 2007) mandate a liquid fuel blending level of about 32 billion gallons (or 121 billion liters). In terms of biomass based electricity today this is an industry largely based on byproducts where pulp and paper byproducts are used as are rice hulls and other agricultural byproducts. However, there are prospects for expanded use of agricultural feedstocks as electrical generation fuel (McCarl et al. 2000; Shackley et al. 2015). According to the Billion-Ton Report from Department of Energy (Langholtz, Stokes and Eaton 2016), US has the potential to provide 1.2-1.5 billion dry tons by 2040 at a price level of $60 per dry ton

In terms of wind and solar based renewable electricity rural lands are generally the platform for such generation, particularly wind. In fact, wind and solar generation has increased dramatically in recent years due to technological progress and materials cost reduction. In the US, more than 60% of the newly added utility-scale capacity as of 2016 was from wind and solar (US EIA 2017c) with the wind almost exclusively in rural areas and much of the solar located there.

In expanding agriculture and rural lands based renewable energy several challenges remain. On the biofuel side, the majority of current ethanol and biodiesel production utilizes first-generation or vegetable oil based feedstocks such as corn, sugarcane and soybean oil, which are also important food and feed crops limiting expansion prospects. Biofuel production based on second generation feedstocks such as agricultural residuals, trees and energy crops is a possible source of expansion but commercialized production is currently constrained by high conversion costs, low feedstock energy density and high feedstock water content the last two of which also limit bioelectricity production prospects (Jones et al. 2017).

On the renewable electricity side, rural lands are widely available but characteristics of the power and generating costs limit expansion. In terms of the power, wind and solar are intermittent generation sources due to variations in wind and sunshine conditions. Thus, power from those generation sources varies from day to day and in the case of solar between day and night and is thus not as reliable as power from fossil fuel sources. As a result, adjustments to existing power system infrastructure and management are needed in terms of energy storage, forecasting, backup capacity, timing of various generation sources etc., which leads to additional cost (Hand et al. 2012). Also, wind and solar costs per unit generated are often higher than are fossil fuel costs but have substantially less external costs (e.g. reduced pollution emissions and GHG emissions). Such external cost savings may need to be valued or conversely the external costs applied to fossil generation to expand solar and wind generation. A detailed discussion of the challenges to increasing renewable electricity penetration is available in Mai et al. (2014).

This dissertation addresses aspects of the aforementioned issues through three essays addressing items occurring at the intersection of agriculture, renewable energy and climate change. Specifically, the following topics will be addressed with a specific focus on production in the US:

- Essay One reports on a study directed at seeing whether incorporation of spatial interrelationships improves identification of the impact of climate change. This is done focusing on Midwest US corn yields.
- Assessing the economics of bioelectricity, wind and solar generation which are forms of climate change mitigation. In particular
  - Essay Two reports on an examination of the consequences of consideration or omission of biorefinery asset fixity characteristics in evaluating liquid fuel market share.
  - Essay Three reports on an analysis of future electricity market share of generation by wind, solar and biomass based electricity under altered technological progress and increased reliability as manifest in lower price discounting for the lower reliability sources. An analysis will also be done on the consequences of pricing carbon emissions from fossil based generation.

CHAPTER II

THE IMPACT OF CLIMATE CHANGE ON CORN YIELD: INCORPORATING SPATIAL INTERRELATIONSHIPS

Introduction

Agricultural production is directly influenced by climate and thus is vulnerable to climate change. A number of studies have examined this vulnerability using econometric approaches (Wallace 1920; Lobell and Asner 2003; Chen, McCarl and Schimmelpfennig 2004; Schlenker and Roberts 2006; Deschênes and Greenstone 2007; McCarl, Villavicencio and Wu 2008; Schlenker and Roberts 2009; Attavanich and McCarl 2014; Miao, Khanna and Huang 2016). Most of these studies use a time series, cross section dataset to estimate the effect of varying climatic conditions (a so-called spatial analogue approach - Adams et al. 1998). However, such approaches may be vulnerable to variables omitted due to data availability or lack of treatment. For example, Schlenker et al. (2005) indicate that omitting irrigation as has been done in a number of studies biases the estimates. Deschênes and Greenstone (2007) suggest that models with irrigation considered still could suffer from other omitted variables.

To deal with the omitted variable issue, a number of studies have used panel data approaches (Chen et al. 2004; Schlenker and Roberts 2006; Deschênes and Greenstone 2007; McCarl et al. 2008; Schlenker and Roberts 2009; Miao et al. 2016). Deschenes and Greenstone (2007) argue that panel models help reduce omitted variable issues by accounting for systematic regional and/or temporal omitted fixed effects such as soil characteristics, socioeconomic factors, and/or major droughts. Blanc and Schlenker

(2017) discuss this issue at length and conclude that panel data models are the preferred approach.

However, panel data approaches also have limitations. Fisher et al. (2012) suggest that fixed effects tend to absorb a significant amount of data variation, which makes the results vulnerable to model misspecification and measurement error. Moreover, while regional fixed effects could account for time-invariant omitted variables, items that vary over time but commonly influence nearby regions would still bias estimates. A similar argument applies to temporal fixed effects. For example, studies are not typically done including data on ground level ozone but ozone incidence is positively correlated with maximum temperatures and varies with time and could commonly impact adjacent regions biasing temperature related estimates (McGrath et al. 2015).

One source of omitted variable bias is omitted climate related variables. Auffhammer and Schlenker (2014) suggest models should also include weather variables like solar radiation, ground level ozone, and wind speed which generally climate influences with common effects in nearby regions that are also different across time. Omission of such items would likely bias estimates of climate impact for the climate variables that are present. In practice, including the universe of such variables is often not possible due to a lack of consistent and high-resolution data. Nevertheless, estimations based on only temperature and precipitation where those items are correlated with omitted climate variables generally provide valuable information as argued by D'Agostino and Schlenker (2016). More generally, the estimates are valuable if the omitted variables are correlated with those included, and their joint distribution remains unchanged over time.

This study is motivated by arguments in the literature that omitted variable biases can be partially overcome by exploiting spatial effects in the estimation residuals (Mur and Angulo 2009). Climate variables tend to be spatially correlated and omitting climate associated variables that have common characteristics over nearby region leads to spatially correlated error terms. Schlenker et al. (2006) recognize this and use the Spatial Error Model (SEM) to handle such issues. Later Ortiz-Bobea (2015) uses a more flexible Spatial Durbin Model (SDM) to better manage the omissions in a cross-sectional study on farmland value. Here we use a SDM in a panel data study on the relationship between climate and crop yield. In that setting SDM is able to aount for temporal and spatial variations in the omitted variables.

This study investigates climate effects on crop yields testing whether incorporating spatial dependence changes estimates and alters out-of-sample performance. The results show strong support for the use of a spatial model that allows for dynamically changing interregional relationships (the SDM model) relative to other commonly used approaches. The results also show a non-linear impact of temperature on corn yield where initially temperature increases benefit yield but extreme heat (above 29ºC) brings significant declines, which agrees with previous literature.

Literature Review

Correlated Omitted Climate Variables and Forecasting

While most climate-yield studies include precipitation and temperature related variables, climate variations may impact yields in other, indirect ways. For instance, ground level ozone, which is influenced by maximum temperature, strongly influences crop yields (Adams, Hamilton and McCarl 1986; Sheffield et al. 2011). Similarly, solar radiation, which is strongly correlated with temperature, is an important yield determinant (Sheehy, Mitchell and Ferrer 2006). The literature also suggests the inclusion of other factors such as the CO_2 fertilization effect (Lobell and Field 2008; Attavanich and McCarl 2014), humidity, wind speed and evaporation (Zhang, Zhang and Chen 2017).

An obvious way to address such omissions is to use a more comprehensive climate dataset. Some recent studies include drought indices, counts of extreme heat days, CO_2, precipitation intensity, El Niño Southern Oscillation effects and other items (Sheehy et al. 2006; Lobell and Field 2008; McCarl et al. 2008; Sheffield et al. 2011; Attavanich and McCarl 2014; Zhang et al. 2017). However, including all of these items in a consistent and high-resolution manner is often not possible (Auffhammer and Schlenker 2014) and to our best knowledge no study has covered all the omitted items discussed above.

On the other hand, if climate variations affect the joint distribution of several influential variables, usage of a small set of climate variables could still yield good forecasts as long as the climate variables used are well correlated with the omitted items

(D’Agostino and Schlenker 2016). Therefore for the purpose of forecasting climate change effects on agricultural productivity, which is the key question in many studies (Deschênes and Greenstone 2007; Mendelsohn, Nordhaus and Shaw 1994; Burke and Emerick 2016), it is acceptable to omit unobserved factors which are highly correlated with the observed ones. Nevertheless, improvements might be achieved by handling such correlation in a better manner.

Spatial Models and Omitted Variables

Several spatial econometric studies have showed that when variables with spatial dependence are omitted the estimates would be biased with the residuals being spatially correlated (McMillen 2003; Fingleton and López-Bazo 2006; Mur and Angulo 2009). Thus, spatial patterns in the residuals generally indicate the presence of spatially dependent omitted variables. While both climate and crop yield data show strong spatial patterns, only a few crop yield/climate studies have incorporated procedures that handle spatially correlated residuals as discussed below.

Schlenker et al. (2006) conduct a climate yield study using the SEM model to handle spatial correlation. That model assumes that error terms are uncorrelated with the independent variables. But if the included independent variables are correlated with the omitted variables and vary over time, the SEM estimates might be biased. To address this issue, one can use a model that accounts for correlation between the error term and the independent variables. The SDM model (Anselin 2013) is such a model. The SDM model decomposes the error term into two components: 1) a component that is a function of the observed independent variables (representing their potential correlation) and 2) an independent and identically distributed random component (LeSage 2008). Under SDM, the estimated coefficients convey not only the direct effects of the independent variables but also indirect effects from the omitted variables. This approach is adopted in this study to explore climate effects on crop yield.

Ortiz-Bobea (2015) is the only paper we have found in the climate-agricultural arena that uses SDM. Ortiz-Bobea (2015) employs SDM in a cross-sectional study of climate effects on cropland value, and found the usage of SDM improved estimation accuracy compared with OLS or SEM. The current study adopts the SDM approach using a panel data spatial and temporal approach. We will also conduct an out-of-sample examination of SDM performance relative to other estimation approaches.

Another factor in our estimation involves functional form specification. There is little doubt that extreme cold or heat will reduce yield to close-to-zero as will extreme rain or no rain (Deryng et al. 2014). This means estimated effects are expected to be take on an inverted U in shape and thus that the functional form should incorporate a nonlinear response. To address this issue, squared terms of climate variables have been included in many studies (Mendelsohn et al. 1994; Cabas, Weersink and Olale 2010; Lobell 2014). However, only including squared terms assumes that the climate impact is symmetric, but Schlenker and Roberts (2009) find an asymmetric response where yields gradually increase with warmer weather but fell dramatically above a threshold. Thus, inclusion of more flexible nonlinear forms appears appropriate. In this study, we use spline functions of temperature to accommodate a flexible relationship between yield and temperature.

Methods and Data

Model Setup

A function describing climate impacts on crop yields can be expressed as follows:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \tag{1}$$

where $\boldsymbol{y}$ is the crop yield, $\boldsymbol{X}$ is a set of independent variables and $\boldsymbol{u}$ is the error term. If there exist omitted variables such that $E(\boldsymbol{X}, \boldsymbol{u}) \neq 0$, an OLS estimate will be biased. Moreover, as previously mentioned, the residuals could show strong spatial dependence due to omitted spatial dependent variables.

The SEM model (see Chapter 3 of LeSage (2008))(2006)accounts for spatial autocorrelation assuming it is of the form $\boldsymbol{u} = \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\epsilon}$, or equivalently, $\boldsymbol{u} = (\boldsymbol{I}_n - \lambda \boldsymbol{W})^{-1} \boldsymbol{\epsilon}$, where $\boldsymbol{I}_n$ is an identity matrix, $\boldsymbol{W}$ is a spatial weight matrix (see more discussion in last paragraph of section 3.2), and λ is a spatial dependence factor that varies between 0 and 1 with a larger value indicating stronger interdependence and $\boldsymbol{\epsilon} \sim N(0, \sigma^2 I_n)$. This yields the following equation:

$$\mathbf{y} = \mathbf{X}\beta + (\boldsymbol{I}_n - \lambda \boldsymbol{W})^{-1} \boldsymbol{\epsilon} \tag{2}$$

The SEM is unbiased when the omitted variables and the independent variables are independent, which may not hold. In particular in our case the omitted variables (e.g. farming practices, ground level ozone, CO_2 and solar radiation) are likely correlated with the climate variables included in $\boldsymbol{X}$. This can be handled using the SDM model which allows the error term to be a function of the independent variables $\boldsymbol{X}$ and random noise $\boldsymbol{\nu}$ such that $\boldsymbol{\epsilon} = \boldsymbol{X}\gamma + \boldsymbol{\nu}$. It follows that equation (2) can be rewritten as follows:

$$\mathbf{y} = \mathbf{X}\beta + (\boldsymbol{I}_n - \lambda\boldsymbol{W})^{-1}(\boldsymbol{X}\gamma + \boldsymbol{\nu})$$

$$(\boldsymbol{I}_n - \lambda\boldsymbol{W})\mathbf{y} = (\boldsymbol{I}_n - \lambda\boldsymbol{W})\mathbf{X}\beta + \boldsymbol{X}\gamma + \boldsymbol{\nu}$$

$$\mathbf{y} = \lambda\mathbf{WY} + \mathbf{X}(\beta + \gamma) + \mathbf{WX}(-\lambda\beta) + \boldsymbol{\nu} \tag{3}$$

Alternatively, this model can be expressed in a reduced form as follows

$$\mathbf{y} = \rho\mathbf{WY} + \mathbf{X}\beta^* + \mathbf{WX}\theta + \boldsymbol{\nu} \tag{4}$$

where the right hand side includes the spatial lag of the dependent variable, the independent variables and the spatial lag of the independent variables (Mur and Angulo 2005). Comparing equations (3) and (4), ρ is a spatial dependence factor that differs from that in the SEM model; β^* and θ are coefficients conveying the direct and indirect effects of the independent variables. Once the reduced form model in equation (4) is estimated one can recover the parameters of in equation (3) as follows

$$\begin{cases} \lambda = \rho \\ \beta + \gamma = \beta^* \\ -\lambda\beta = \theta \end{cases} \tag{5}$$

While the interpretation of coefficient β in equations (1) and (2) is straightforward, things are more complicated in the SDM model with the introduction of the spatial dependence ($\boldsymbol{WX}$). Under the SDM, a change in the independent variables in one region affects not only that region (direct effect) but also nearby regions (indirect effect). Mathematically, the response of $\boldsymbol{y}$ (yield) to changes in $\boldsymbol{X}$ (climate variables) is given by:

$$\boldsymbol{S}_r \equiv \frac{\partial \boldsymbol{y}}{\partial x_{nk}} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}(\boldsymbol{I}_n \beta_r{}^* + \boldsymbol{W}\theta_r) \tag{6}$$

$$= (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1} \begin{bmatrix} \beta_k{}^* & w_{12}\theta_k & \cdots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k{}^* & & w_{2n}\theta_k \\ \vdots & & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_k{}^* \end{bmatrix}$$

where $n \in [1, \dots, N]$ identifies spatial region, and $k \in [1, \dots, K]$ the set of independent variables. The $N \times N$ $\boldsymbol{S}_r$ matrix contains partial derivatives that capture the impact of the independent variable on the dependent variables in and across regions. According to LeSage (2008), the average direct impact, which depicts the impact of changes in x_k in region *n* on the dependent variable in region *n*, could be measured by averaging the diagonal elements of $\boldsymbol{S}_r$, or $N^{-1}tr(\boldsymbol{S}_r)$. The total impacts could be calculated as $N^{-1}\iota_n'\boldsymbol{S}_r\iota_n$, i.e. the summation of $\boldsymbol{S}_r$ divided by the number of regions where ι_n is a vector of 1's. The indirect impacts are given by the difference between the total and the direct impacts. In the context of climate change and yield, the direct effect captures the impact of observed independent variables (e.g. temperature and precipitation) while the indirect effect captures the impact of the omitted variables across space.

The SEM model is nested in the SDM model. Namely when γ in equation (3) is zero. Similarly, the standard linear model is nested within the SEM when λ in equation (2) equals zero. We shall use formal statistical tests to test whether this is the case in our empirical analyses below.

Belotti et al. (2013) used the SEM and SDM models in a panel data setting as will we. The general formula for yield in region *n* year *t* is given in equation (7) and can be estimated using the maximum likelihood approach used by Belotti et al. (2013).

$$y_{nt} = \rho \boldsymbol{W} y_{nt} + \beta x_{nt} + \theta \boldsymbol{D} x_{nt} + \phi_n + \varphi_t + u_{nt} \qquad (7)$$
$$u_{nt} = \lambda \boldsymbol{E} u_{nt} + v_{nt}$$

where ϕ_i and φ_t are the individual- and time-specific effects, u_{nt} is a spatially correlated error and v_{nt} is a normally distributed error. W, D and E are all N×N spatial weight matrices identifying adjacent regions (their formation is discussed in section 3.2) that could be identical or differ depending the context (they are identical here). When $\rho = \theta = \lambda = 0$, equation (7) reduces to the conventional panel model; while $\rho = \theta = 0$ gives the SEM model, and $\lambda = 0$ gives the SDM model.

Methodology

We will do our estimation on corn yields. The yields we use are calculated from data drawn from the United States Department of Agriculture's National Agricultural Statistics Service (USDA NASS) Quick Stats 2 database. Corn yield per harvested acre is constructed at county level by dividing the total county corn production by the corn acres harvested. We use data from the years 1950-2015. To minimize the influence of irrigation we only use data from east of the 100º meridian following (Schlenker and Roberts 2009; Burke and Emerick 2016). The consequent data set contains 51,612 observations from 782 counties (see Fig. 1 for a map of these counties) over 66 years and is a balanced panel dataset.

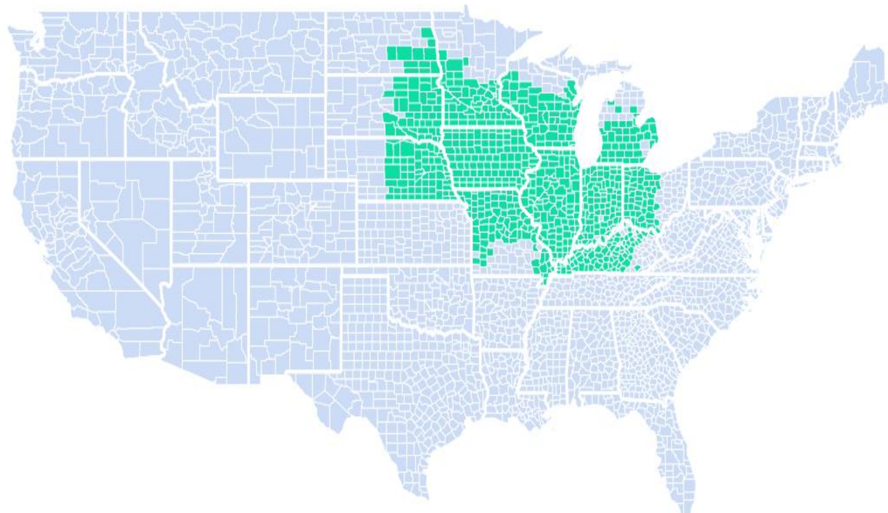

Figure 1. Study region in green

The climate data we use are drawn from Schlenker and Roberts (2006) using their updates to 2015 which include county-level precipitation and temperature during the growing season (between April 1st and September 30th). Specifically, temperature information is measured by a series of Degree Day (*DDay*) variables that reflect the cumulative temperature above certain thresholds during the growing season. For example, *DDay0c* stands for the cumulative degrees above 0ºC. The thresholds range from 0ºC to 34ºC. We report the summary statistics on the data in Table 1.

Table 1. Summary statistics

*Variable**	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
log(cornyield)	51,612	4.49	0.49	-1.20	5.46
precipitation	51,612	57.10	14.09	13.67	127.22
DDay0c	51,612	3,413.26	343.86	2,337.50	4,461.68
DDay5c	51,612	2,528.00	326.37	1,525.35	3,549.87
DDay10c	51,612	1,701.31	289.36	848.48	2,651.38
DDay15c	51,612	985.75	227.62	365.41	1,820.20
DDay20c	51,612	452.90	145.22	84.91	1,100.35
DDay29c	51,612	35.27	29.57	0.01	291.65
DDay34c	51,612	2.09	4.51	0.00	91.20
					782 counties, 1950-2015

* corn yield (bushel/acre), precipitation (cm) and DDAY (accumulated ºC for all days above threshold).

For illustration purpose only Fig. 2 shows the study region distributions of corn yield, precipitation and degree days (for thresholds of 10ºC and 29ºC) averaged over years 2011-2015. There we see corn yield is highest in the Corn Belt, especially in Illinois and Iowa. We also see that precipitation generally decreases from east to west and the degree days increase from north to south. It is worth noting that the temporal averages as shown in Fig. 2 smooth out substantial variation and we use the individual years in our estimation. The large number of observations in the panel dataset also allows us to reserve data for examining out-of-sample forecast performance. In this study, we estimate our model using the data from the period 1950-2010 and reserve the data from 2011-2015 for out-of-sample validation.

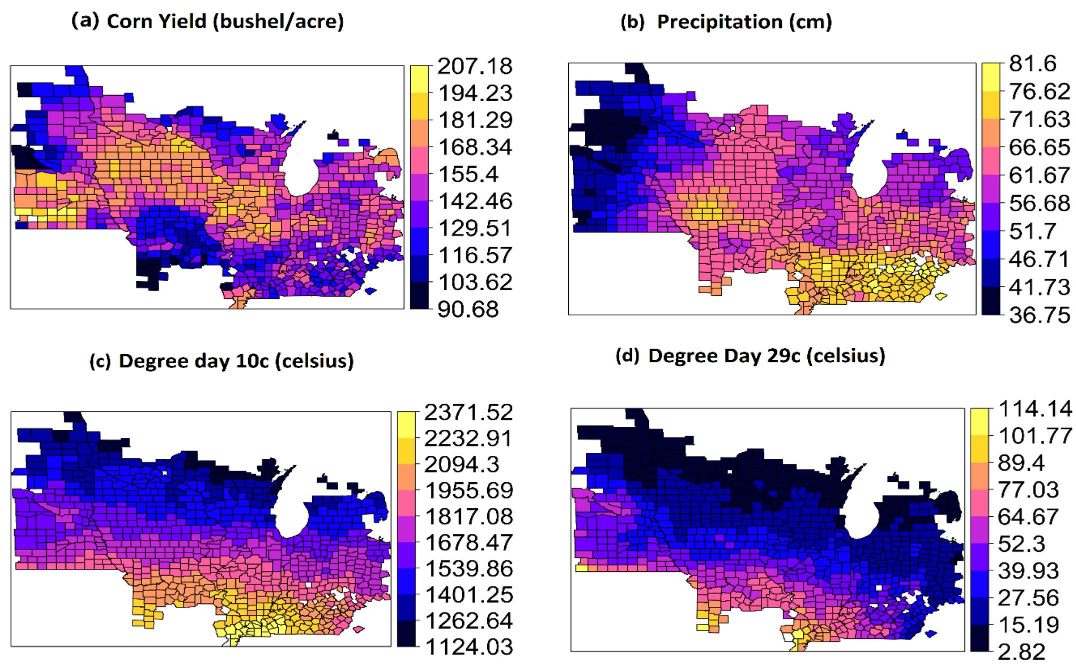

Figure 2. Spatial distribution of mean county level yield, precipitation and degree days over growing season in the study region as depicted in Figure 1, 2011-2015

There are a few estimation procedure details meriting explanation before we report the results. First, we use log corn yield as the dependent variable instead of corn yield following Schlenker and Roberts (2009) and Burke and Emerick (2016). Lobell and Burke (2010) indicate the use of the log assumes that a level of change in the independent variables has the same percent impact on yield regardless of yield level. Second, seven degree-day variables are used for temperature allowing for more flexibility depicting the potential non-linear asymmetric impact of temperature on corn yield which constitutes a linear spline with 6 knots.

Lastly, we form the SEM and SDM spatial weight matrices following Fischer and Getis (2009). Under that specification if the nth region has z neighboring regions, then the nth row of the spatial weight matrix will have zeros for all non-neighboring regions and 1/z for each of the z neighboring regions (thus each neighbor is given the equal weight).

Empirical Results

OLS and Panel Non-spatial Estimation Results

For the sake of comparison, we first estimate the corn yield effects using conventional models namely pooled OLS and fixed effect panel models. Two basic model specifications are analyzed using different sets of degree day variables. The first specification includes only two degree day variables (i.e. *DDay0c* and *DDay29c*), following Schlenker and Roberts (2009) and Burke and Emerick (2016). This assumes that growing degree days above 0ºC and hot days (those above 29ºC) have differential effects. The second specification includes seven degree-day variables (i.e. linear spline with 6 knots with an interval of 5 ºC) and permits more flexible temperature effects. The resultant regression results are summarized in Table 2.

Table 2. Pooled OLS and panel regression of log corn yield on weather variables

	OLS_1knots	OLS_6knots	Panel_1knots	Panel_6knots
dday0C	0.0004***	0.0043***	0.0004***	-0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)
dday5C		-0.0056***		0.0030***
		(0.000)		(0.000)
dday10C		0.0033***		-0.0022***
		(0.000)		(0.000)
dday15C		-0.0036***		-0.0012***
		(0.000)		(0.000)
dday20C		0.0026***		0.0026***
		(0.000)		(0.000)
dday29C	-0.0078***	-0.0067***	-0.0077***	-0.0083***
	(0.000)	(0.000)	(0.000)	(0.000)
dday34C		-0.0100***		-0.0088***
		(0.001)		(0.001)
prec	0.0261***	0.0256***	0.0165***	0.0165***
	(0.000)	(0.000)	(0.000)	(0.000)
prec^2	-0.0002***	-0.0002***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
t	0.0183***	0.0183***	0.0184***	0.0185***
	(0.000)	(0.000)	(0.000)	(0.000)
t^2	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.6978***	0.4215***	2.9795***	3.3690***
	(0.019)	(0.101)	(0.029)	(0.086)
R^2	0.7359	0.7412	0.8190	0.8228
d.f.	47695	47690	46914	46909
out-of-sample RMSE	0.257	0.250	0.253	0.244

* the asterisks denote the probability that the coefficient differs from zero with three levels of significance where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The estimates from the pooled OLS and fixed effect panel models are similar. Although fixed effect panel model estimates exhibit smaller climate effects, it is plausibly due to omitted variable effects being picked up in the fixed effects terms. Both the R^2 and out-of-sample Root Mean Squared Errors (RMSE) suggest that the fixed effect panel estimator with the larger number of degree day independent variables is the preferred model.

Fig. 3 contains a plot of the estimated relationship between the degree day variables (which represent temperature effects) and the percent change in log corn yield. The figure clearly shows a non-linear and asymmetric impact of higher temperatures on corn yields, wherein the yield gradually increases starting from 0ºC as more warm weather occurs and then decreases significantly as the temperatures pass the 29ºC threshold. The result is comparable to the findings in the literature (e.g. Schlenker and Roberts (2009) and Burke and Emerick (2016)).

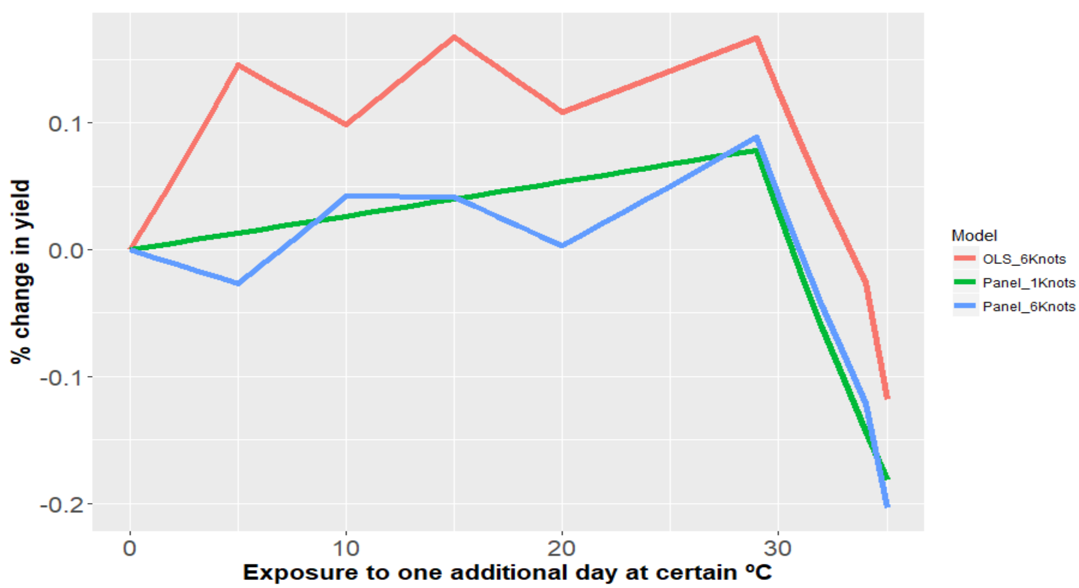

Figure 3. Relationship* between temperature and corn yield

* Estimates represent the change in corn yield due to one additional day of exposure to a given ºC temperature relative to a day with temperature 0ºC. Results for model OLS_1Knots is omitted as it is almost identical to those from model Panel_1Knots.

Spatial Dependence in the Residuals from Non-spatial models

We next examine whether there is spatial dependence in the residuals using the Pesaran test (Pesaran 2004). This test is based on the pair-wise interregional correlation coefficients as follows

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{8}$$

where $\hat{\rho}_{ij}$ is the correlation coefficient in the residuals between regions i and j, T is the number of years and N is the number of regions. The test statistic follows the standard normal distribution asymptotically.

We calculated this test statistic for the residuals arising from panel model with the seven degree day independent variables. The hypothesis of the no spatial correlation is rejected at the 0.01 level of significance. Thus, there is strong evidence for spatial correlation in the residuals from the fixed effect panel model. This likely indicates the model suffers from omitted, spatially correlated independent variables and we now turn to use of the SEM and SDM models.

Spatial Estimation Results

Given the preceding finding of spatial dependence in our model, we proceed to SEM and SDM estimation. We estimate these models using the full set of seven-degree day variables and other variables used in the non-spatial panel model. The estimation results are summarized in Table 3 that also includes the panel model results for comparison. The degree day effects from the panel, SEM and SDM models are shown in

Fig. 4. Note that the SEM results are directly comparable to the panel results while SDM results need manipulation to account for both direct and indirect effects as computed via equation (6).

Table 3. Panel, SEM and SDM estimation results of log corn yield on weather variables

	Panel	SEM	SDM
Main			
dday0C	-0.0009***	0.0003	0.0021***
	(0.00)	(0.00)	(0.00)
dday5C	0.0030***	0.0002	-0.0028**
	(0.00)	(0.00)	(0.00)
dday10C	-0.0022***	0.0005	0.0011
	(0.00)	(0.00)	(0.00)
dday15C	-0.0012***	-0.0021***	-0.0006
	(0.00)	(0.00)	(0.00)
dday20C	0.0026***	0.0018***	-0.0000
	(0.00)	(0.00)	(0.00)
dday29C	-0.0083***	-0.0053***	-0.0026***
	(0.00)	(0.00)	(0.00)
dday34C	-0.0088***	-0.0034**	0.0002
	(0.00)	(0.00)	(0.00)
prec	0.0165***	0.0144***	0.0123***
	(0.00)	(0.00)	(0.00)
$prec^2$	-0.0001***	-0.0001***	-0.0001***
	(0.00)	(0.00)	(0.00)
t	0.0185***	0.0190***	0.0025***
	(0.00)	(0.00)	(0.00)
t^2	-0.0002***	-0.0002***	-0.0000***
	(0.00)	(0.00)	(0.00)
Constant	3.3690***		
	(0.09)		
Spatial			
λ		0.8781***	
		(0.00)	
ρ			0.8649***
			(0.00)

Table 3 Continued

	Panel	SEM	SDM
Wx			
dday0C			-0.0023***
			(0.00)
dday5C			0.0033**
			(0.00)
dday10C			-0.0014
			(0.00)
dday15C			0.0005
			(0.00)
dday20C			0.0004
			(0.00)
dday29C			0.0015*
			(0.00)
dday34C			-0.0020
			(0.00)
prec			-0.0098***
			(0.00)
$prec^2$			0.0001***
			(0.00)
$\mathbf{R^2}$	0.8228		

* the asterisks denote the probability that the coefficient differs from zero with three levels of significance where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Under the SEM model the spatial parameter, λ, equals 0.88 which is significantly different from 0, indicating a strong presence of spatial correlation with a finding that 88% of the effects in one region times the spatial weights are transmitted to the nearby regions. We also note that the SEM estimated effects of climate are generally smaller than the panel estimates, as the spatial error structure passes part of that effect to nearby regions. Additionally, the climate coefficients broadly agree with the panel model in terms of sign and for the most part statistical significance although some of the SEM degree day variables are insignificant.

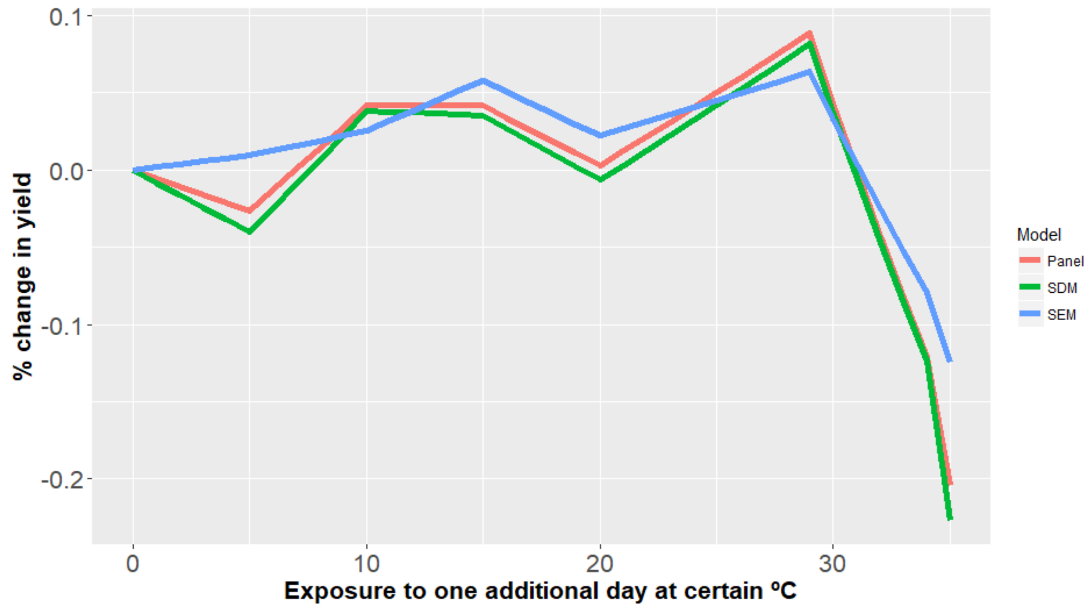

Figure 4 Relationship between temperature and corn yield from spatial model estimation

We next turn to the SDM results. As mentioned earlier, the estimated coefficients in column 3 of Table 3 include both the direct and indirect, cross-region, effects. As a result, we calculate the $\boldsymbol{S}_r$ matrix in equation (6) and use it to derive the direct and indirect impacts, which are in Table 4.

Table 4. Direct and indirect effects of climate variables on log of corn yield derived from the SDM regression result (with SEM results for comparison)

	SDM			SEM
	Direct	**Indirect**	**Total**	
dday0C	0.0019***	-0.0032***	-0.0013	0.0003
	(0.00)	(0.00)	(0.00)	(0.00)
dday5C	-0.0025**	0.0063***	0.0038*	0.0002
	(0.00)	(0.00)	(0.00)	(0.00)
dday10C	0.0009	-0.0035*	-0.0026	0.0005
	(0.00)	(0.00)	(0.00)	(0.00)
dday15C	-0.0007	-0.0005	-0.0012	-0.0021***
	(0.00)	(0.00)	(0.00)	(0.00)
dday20C	0.0002	0.0026**	0.0028**	0.0018***
	(0.00)	(0.00)	(0.00)	(0.00)
dday29C	-0.0029***	-0.0054***	-0.0082***	-0.0053***
	(0.00)	(0.00)	(0.00)	(0.00)
dday34C	-0.0006	-0.0127***	-0.0133***	-0.0034**
	(0.00)	(0.00)	(0.00)	(0.00)
prec	0.0127***	0.0059**	0.0186***	0.0144***
	(0.00)	(0.00)	(0.00)	(0.00)
$prec^2$	-0.0001***	-0.0001***	-0.0002***	-0.0001***
	(0.00)	(0.00)	(0.00)	(0.00)
t	0.0034***	0.0153***	0.0187***	0.0190***
	(0.00)	(0.00)	(0.00)	(0.00)
t^2	-0.0000***	-0.0002***	-0.0002***	-0.0002***
	(0.00)	(0.00)	(0.00)	(0.00)

* the asterisks denote the probability that the coefficient differs from zero with three levels of significance where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The decomposition of the total effects is illustrated in Figure 5, wherein the solid red line shows their sum and is the same as the SDM line in Fig. 4. The indirect effects are from the transmission of effects from other regions as we discussed earlier. Without knowing the source and nature of the omitted variables, no definite explanations can be given to their causal factors. Nonetheless, separating the direct and indirect effects does provide more consistent estimation of temperature impacts (namely the direct component) and are graphed in Fig. 5 along with their sum. Here we find the basic nature of the summed effects from the SDM estimates are similar to those found in the estimates from the panel and SEM models (Fig. 4).

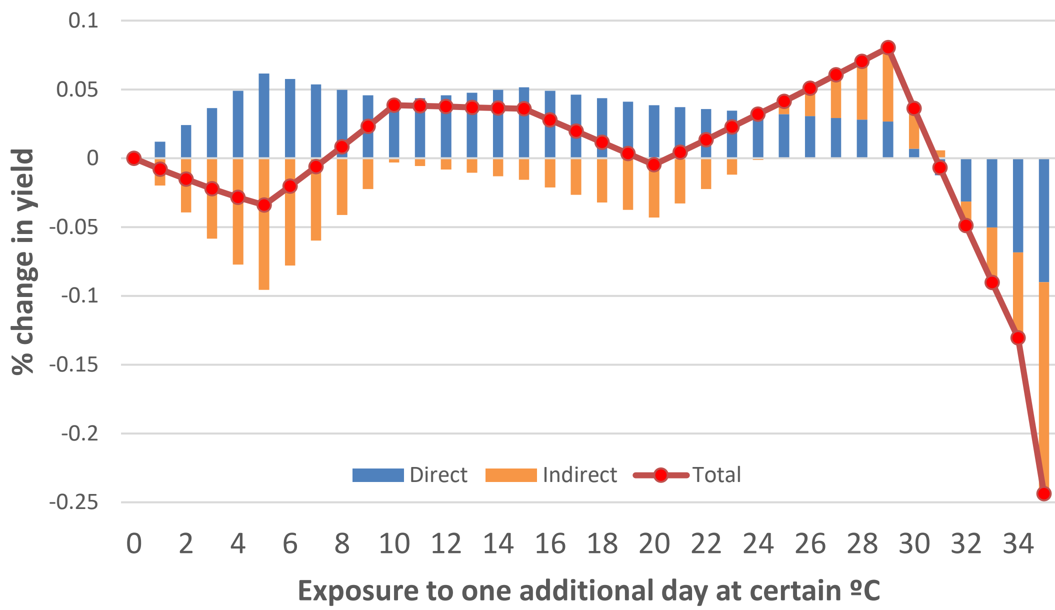

Figure 5. Percent change in crop yields as for degree days at given thresholds from SDM decomposition

Model Comparison

Conventional model selection criteria such as R^2 or Akaike information criterion cannot be applied directly here as the Panel model is estimated with least squares while the SEM/SDM models are estimated through maximum likelihood. Moreover, even the likelihood functions of SEM and SDM model are not directly comparable as different data transformation procedures are applied. We therefore use out-of-sample RMSE to compare these competing models, which also evaluates model forecasting power. As mentioned before, data from 2011-2015 were held out for out-of-sample model evaluation. The results are reported in Table 5.

Table 5. Out-of-sample root mean squared error

Data Used	**Panel**	**SEM**	**SDM**
2011-2015	0.24	0.23	0.22
Only 2012	0.40	0.39	0.35

The out-of-sample RMSEs calculated for the extrapolated values calculated from the panel, SEM and SDM estimates are 0.24, 0.23, and 0.22, respectively. This indicates that SDM improves the prediction accuracy by more than 8% compared with the panel model and 4% compared with the SEM model. We also assess the forecasting power under extreme weather conditions using only 2012 data, which was a severe drought year in the Corn Belt. Again, the RMSE is smallest in the SDM forecast at 0.35, followed by SEM at 0.39 and panel at 0.40. In both cases, the SDM model outperforms the SEM and panel models.

Additionally, we use statistical tests on the parameters that differentiate the model specifications. The first test addresses whether the spatial dependence factor in the SEM estimates is not different from zero ($\lambda = 0$ in equation 2), under which the SEM model reduces to the conventional fixed effects panel model. This is rejected at 0.01 confidence level leading to a preference for the SEM model over the panel model.

Similarly, when γ in equation (3) equals zero the SDM model reduces to the SEM model. A direct test on γ is not available as the reduced form does not contain γ. However, it is easy to see from equation (5) that when $\gamma = 0$ we have $\beta^* = \beta$ thus the last formula in equation (5) becomes $\theta + \rho\beta^* = 0$. Estimated values and standard errors for all of these parameters are available thus a Wald test is performed on the null hypothesis that the SEM model is preferred over the SDM model. P-value of the test is nearly zero, strongly favoring the SDM model that controls for correlation between the independent and unobserved variables.

Lastly, we examine the residual distributions across the specifications as portrayed in Fig. 6, which depict the estimated densities developed with the Gaussian kernel density estimator. The red line shows the residuals distribution from the Panel estimation while the green line is from the SDM estimation[1]. There we see that the residuals from the spatial model exhibit a noticeable reduction in dispersion and are largely free of skewness. In contrast, the residuals from the panel model are more dispersed and are skewed, plausibly due to some omitted variables not accounted in the estimation.

[1] Note we do not graph the residual distribution from the SEM model as it is so close to the SDM residual distribution that it is virtually indistinguishable and similarly the pooled OLS residuals are omitted as they are very close to those from the panel model.

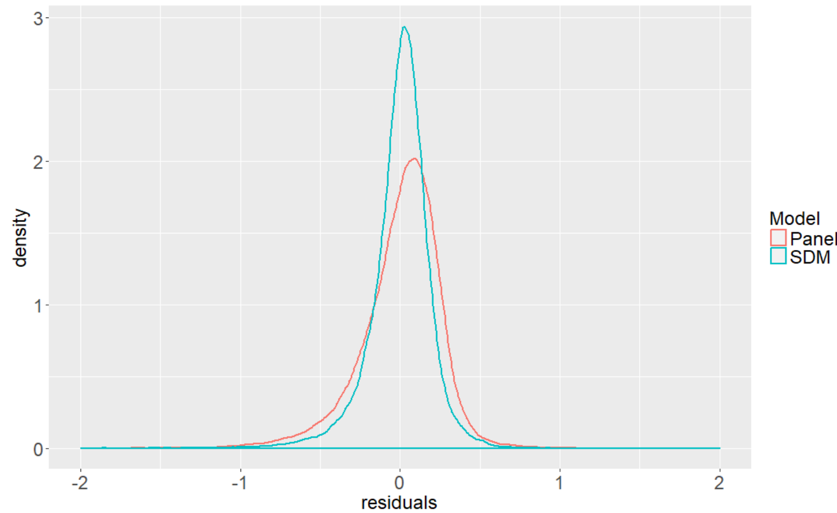

Figure 6. Residual distributions from different models

In sum, incorporating spatial structure improves out of sample forecasting performance. Between the two spatial models, we find the SDM model is preferred. This shows the data apparently exhibit both spatial dependence and correlation of omitted variables with the independent variables.

Discussion and Conclusion

This study is motivated by statements in the literature that capturing the influence of spatially dependent omitted variables will improve model performance and the advancement of models like SEM and SDM to do that. Our estimation results clearly show including spatial considerations leads to improved model fit.

In particular, we find for identifying climate effects on corn yields in the US Corn Belt that using a spatial model improves out-of-sample prediction relative to a conventional panel approach. We also find including a model that allows for spatial dependence across regions and with the independent variables (SDM) performs better than a model that only assumes a fixed spatial dependence between regions (SEM).

We also find the SDM approach performs substantially better under extreme weather conditions – using data from the 2012 extreme corn belt drought year. Furthermore, formal statistical tests on the significance of key model parameters that address spatial characteristics and interdependence of errors and the independent variables support the superiority of the SDM and thereby the existence of spatially dependent omitted variables. Also, residual diagnostics find favor the inclusion of the spatial structure via SDM reduces error term dispersion and skewness. Moreover, the SDM allows improvements in model results interpretation by allowing decomposition of effects into direct and indirect spatially transferred effects. All of this considered, we recommend the SDM model as an technique that should be strongly considered for use in future crop yield/climate studies.

Finally, we should note that estimation results from both the SDM and SEM approaches do not fundamentally change the results on or interpretation of climate effects on yields. We reaffirm the finding of a non-linear and asymmetric inverse-U shaped relationship between yield and temperature as advanced in Schlenker and Roberts (2009). We find temperature impacts peaking around 29ºC and turning negative beyond that. We also find an inverse-U shaped effect of precipitation as also found in Schlenker and Roberts (2009).

CHAPTER III

ASSET FIXITY AND ECONOMIC COMPETITIVENESS OF US ETHANOL PRODUCTION

Introduction

A number of studies have been done on ethanol market penetration and the effects of alternative portfolio of regulation complying feedstocks. These include several used in EPA rulemaking (Beach and McCarl 2010; US EPA 2010). However, a detailed examination of the results in such studies shows the model solutions exhibit and unrealistic shift in patterns of feedstocks used and ethanol production locations between adjacent five-year periods. In particular, while one feedstock will be used in a place in one five-year period the pattern in the next period shows a different feedstock being used in a different place without any carryover of the feedstock/place characteristics from the earlier period. Such a result occurs because the model (FASOM in the case we examined (Beach and McCarl 2010; Adams et al. 2005; Lee et al. 2007)) ignores asset fixity. Namely an ethanol processing plants once built is fixed in location and to a substantial degree is fixed in technology employed, cost structure and feedstock mix it can accept. The general issue is that ignoring such characteristics of asset fixity (AF) and we feel ignoring it may leads to unrealistic patterns of biorefinery location and feedstock mix likely biasing the potential for and competitiveness of ethanol production.

The objective of this study is to assess how much of a difference consideration of asset fixity makes in terms of model predicted ethanol market penetration, feedstock mix and production cost.

Literature Review

Asset fixity has long been a concern of agricultural economists. Gardner (1992) summarized the basic concept indicating that once a choice was made to undertake an investment in a particular asset, the asset becomes fixed in place and class of feedstocks used and would continue to be committed to the use for which it was acquired until the expected return falls to the disposal or salvage value. Johnson (1956) apparently did the original agricultural work on AF motivated by the writings of Johnson (Johnson 1950). In turn the AF concept was formalized by Edwards (1959) and Johnson and Quance (1973). The concept has been considered in number of agriculturally-related analyses (Chambers and Vasavada 1983; Nelson, Braden and Roh 1989; Hsu and Chang 1990).

A closely-related concept to AF was putty-clay technology which arose out of the work of Johansen (1972). Fuss (1977) indicated that a basic question related to the study of technology was the extent to which the flexibility of production possibilities was affected by previous technology choices. He went on to illustrate this in terms of energy price increases in the early 70s and the incentives they created for substitution of other factors production for energy. In that context he indicated that the time path of the adjustment depended upon the ex post flexibility of energy intensive techniques that had already been adopted.

In the context of the biofuel based study reported on herein AF means that ethanol and biodiesel refineries once built are fixed in location and in the general class of feedstocks that can be used. There are certainly reasons to suspect that AF will have major effects on model projections. Atkeson and Kehoe (1999) showed that the putty clay or asset fixity approach helped explain the gradual shifts in energy use in response to persistent changes in energy prices. Additionally, Rajagopal and Zilberman (2013) indicated that asset fixity – putty-clay caused the situation where switching from one technology to another required costly capital investment and that consequently producers had limited flexibility to adjust. Although AF constrains such as location and feedstock types are commonly considered in biorefinery supply chain designs (i.e. determining the optimal location, feedstock and supply chain for a case study area) (Yu et al. 2014; You et al. 2012), to our best knowledge it is not included in existing national-level modeling studies on the biofuel market penetration.

Another related theory was that of irreversible investment under uncertainty (Dixit and Pindyck 1994) which shows that it might be best to delay decisions so as to allow one to obtain better information about such things as processing technology, feedstock cost and other costs. Furthermore, Skevas et al. (2016) showed the investment irreversibility and uncertainty coupled to dampen incentives to invest.

One can also look at AF implications graphically from the supply side as in Fig. 7. Suppose ethanol demand is D and the supply curve from currently operating plants is SS in panel a. Note this reaches the inelastic portion at existing plant capacity (Q_0) and would lead to a high ethanol price (P_0). Now suppose we include the possibility of building a new plant. In that case suppose we assume that the potential owner believes the added plant will operate at a volume of K and the amortized fixed cost is A. Then the supply curve would kink at the volume jumping up in price by A/K then proceeding out to deliver more supply at the marginal cost curve but with A/K added at all volumes (as in panel b). Note once built the new plant falls into the existing plant category in subsequent years where the supply curve is independent of fixed cost as in panel c with the new existing supply becomes SS'.

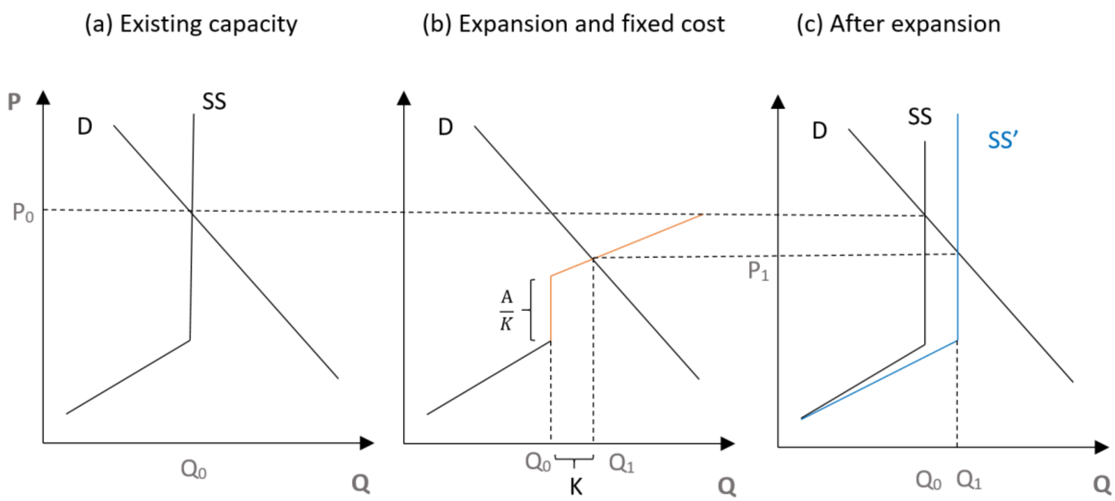

Figure 7. Visual representation of asset fixity concept.

Furthermore several aspects of the situation are not shown in the graphical framework. First, the existing plants create a fixity not only due to plant capacity but also in location and feedstock use flexibility. The new capacity can only operate in the region where it is constructed and generally, the available technology limits feedstock use to a given class of feedstocks for which the plant was initially constructed. Second, the supply curve for new plants is flatter than that for existing plants to reflect the fact that larger capacities can be reached by constructing new plants while the existing facilities have a steeper cost curve since they can only raise production by employing more expensive forms of operation within the bounds of their existing capacity. Third, if new capacity were constructed in period 1 then there would also be a shift in the existing capacity supply curve in period two again making entry for new plants yet harder. Furthermore, in a dynamic sense as the situation progresses through time, more plants are constructed expanding the existing capacity category in the period of construction and subsequent periods up until the point at which the plant becomes functionally obsolete.

Material and Methods

Modeling of Asset Fixity

In the modeling, we introduced asset fixity into the agricultural sector component of FASOM. FASOM has been extensively used in U.S. agricultural and bioenergy related studies including those supporting US rule making under the 2007 EISA act (e.g. Beach and McCarl (2010)). Here, we mainly discuss the inclusion of AF in the model. Readers wishing to know more details on FASOM should examine the work of Beach and McCarl (2010), and Adams et al. (2005).

In FASOM before including AF, the processing component of the ethanol production cost was specified as a feedstock dependent per unit cost based on NREL and EPA estimates, which was the sum of both fixed facility construction cost and variable operating cost. In turn, the FASOM model decided where to locate processing facilities and selected the feedstock type without any consideration of what was used and where it was used in earlier times. As a result, unrealistic projections might occur (e.g. switchgrass ethanol is produced in one region at specific time and in the next period replaced by corn ethanol). In modeling AF for this study, the per unit processing cost was separated into fixed construction cost (which accounts for 35% of the total processing cost) and variable cost components (65%). Accordingly, the processing terms in the model separated into construction component that supplied capacity for the next 30 years paying an upfront construction cost and a capacity utilization component that required capacity from the capital investments or any pre-existing facilities. In addition, in the pre-asset fixity version cellulosic ethanol production costs declined at the rate specified in the projections from NREL. In the asset fixity version, the capital costs were incurred in a time period and they declined following the NREL assumptions.

Empirically 35% of the costs projected per unit by NREL were imposed as incurred in the period of construction. These costs were declining over time as the capital costs involved as the industry became mature according to the assumptions used in NREL. In addition, the operating costs were held at the levels in place at the time the facility was constructed. Further, feedstock utilization possibilities were defined into a number of categories allowing plant to process feedstocks with similar characteristics (see details in the Appendix).

Operationally, this was done by augmenting FASOM with a plant construction variable, $\mathrm{Z}_{t,reg,class}$ representing the amount of newly-build bioenergy capacity constructed in period t in region reg that uses feedstocks in the group class. In turn annual ethanol production, $Y_{t,reg,process,class}$, was constrained by the cumulative previously built and any newly built capacity as in equation (1).

$$\sum_{\substack{process \\ \in p(class)}} Y_{t,reg,process,class} \leq \sum_{\substack{tt=t-k \\ tt-k>0}}^{t} CAP_{class}\, Z_{tt,reg,class} \tag{9}$$

$$+ \sum_{\substack{tt=t-k \\ tt-k\leq\leq 0}}^{t} CAP_{class} ZP_{tt,reg,class}$$

Where the capacity is summed across all previously constructed plants in the previous k years where k is the economic life of bioenergy plants, $process$ is the specific bioenergy production process (e.g. grain dry mill or switchgrass based cellulosic) and CAP_{class} is the capacity of plants built to handle feedstocks of type class. The capacity also includes plants that exist when the model starts up.

Facility capacity differs by feedstock class. The class index permits a plant to process several similar feedstocks. For example, dry mill plants could process corn and sorghum (see the feedstock to class assignment in Table A1).

Finally, cost estimates needed to be separated into fixed and variable components. In this study, based on an examination of NREL documents we assumed that the fixed capital cost accounted for 35% of the per unit processing cost used in the pre-AF model version and multiplied that cost by total plant capacity to get annual fixed cost and put that to a single period cost in the period when the plant was constructed. We then applied the discount rate to get the net present value.

Finally, a maximum rate of new construction was also incorporated. In reality, the annual amount of ethanol production in U.S. has risen to about 57-billion-liter level which is the maximum that falls under the EISA RFS2 and also a volume about equaling

10% of existing gasoline use. In particular, annual consumption of gasoline in the U.S. was around 545 billion liters by 2017 (US EIA 2018), leading to a maximum domestic ethanol consumption of about 53 billion liters if only E10 gasoline was available. In fact, this volume serves as a form of the blend wall limiting domestic consumption and the U.S. has turned from a net ethanol importer to an exporter ever since that volume was reached (Renewable Fuels Association 2017). New investments in blender pumps, storage tanks, higher blend using vehicles, drop in fuels and other infrastructure were needed to increase ethanol market penetration. In FASOM, this were captured by imposing an increasing penetration cost for ethanol production above 57 billion liters based on EIA data. The penetration cost exhibited an upward sloping schedule with higher and higher costs incurred as additional quantities of ethanol were entered into the marketplace. These were derived by looking at EIA assumptions on the cost of ethanol production and consumer price changes as the ethanol penetrated further into the marketplace.

Scenarios Setup

Base Scenarios

Several scenarios were run. First, to examine the impact of AF we ran a no RFS2 scenario with and without AF. Moreover, in the non-AF scenario we removed existing capacities[2].

RFS2 Scenarios

Second, we examined effects of AF in a setting where the Renewable Fuel Standard (RFS2) existed. Scenarios were run with and without AF requiring a maximum of 57 billion liters of corn ethanol and a minimum of 49 billion liters of cellulosic ethanol[3] to be produced by 2022 according to the RFS2 target.

Price Scenarios

Finally, we conducted several ethanol price scenarios in order to assess the level of price needed to make cellulosic ethanol economically competitive in a mandate-free market situation. Specifically, we examine market penetration under a range of ethanol prices ($0.48, $0.79, and $1.06 per liter, or $1.8, $3 and $4 per gallon) with the price escalating at the rates projected in AEO 2016 (see Fig. 8). The model setup in this case did not have RFS2 mandates imposed but did have the NREL projected reductions in cellulosic ethanol production costs.

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[2] Activating the existing capacity in the AF scenario would make ethanol processing cost cheaper than the non-AF scenario since the cost for existing capacity was sunk cost and not reflected in the model objective function.

[3] RFS2 requires 61 billion liters (16 billion gallons) of cellulosic biofuel by 2022. Here we require 49 billion liters (13 billion gallons) of cellulosic ethanol assuming the rest is fulfilled by advanced biodiesel production.

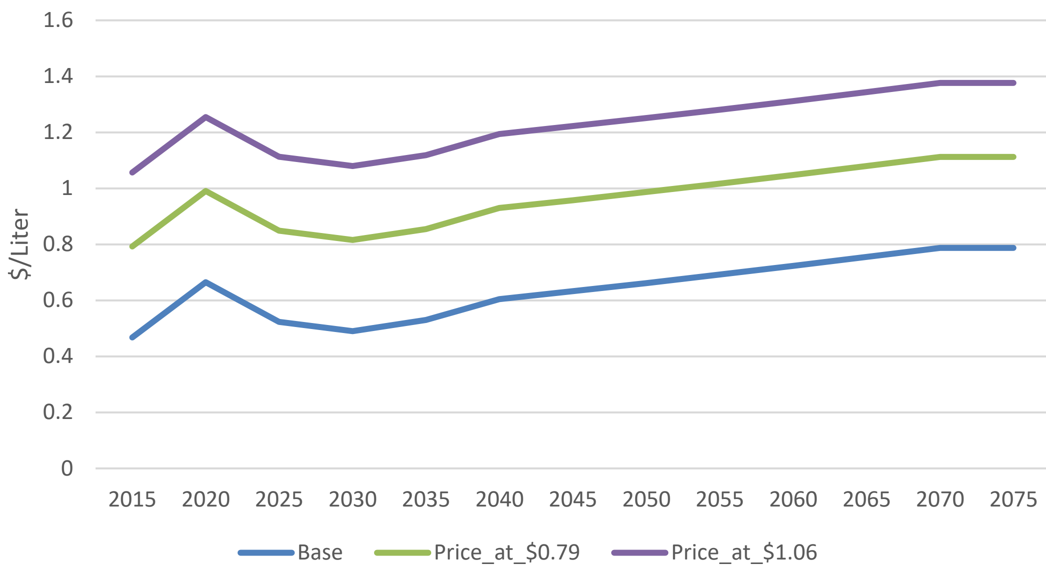


Figure 8. Ethanol price projection scenarios based on AEO 2015

Results

Base Scenario Results

Fig. 9 shows the ethanol production by feedstock in the absence of mandates with and without AF. In both scenarios ethanol production is projected to increase over time due to two major drivers within the FASOM model. First, ethanol price is projected to increase over time as pictured in Fig. 9 according to AEO2015. Besides, continues technology progress in agriculture sector is assumed in FASOM (as reflected by the crop yields) which benefits feedstock supply for ethanol production.

Significant difference is observed between the AF and non-AF scenarios. With AF present, the total amount of conventional crop ethanol increased to 95 billion liters by 2050. No cellulosic ethanol production was projected under AF. When AF was not applied, amount of crop ethanol production increased to 114 billion liters by 2050. About 1.514 billion liters of cellulosic ethanol were also projected (about 0.83 billion from switchgrass, 0.57 billion from bagasse and the rest from agricultural residues) between 2020 and 2035. This shows market-driven ethanol production breaks the blend wall when neglecting AF, meaning omitting AF biases upwards the market potential of cellulosic ethanol.

Figure 9. Ethanol Production by feedstock in base scenarios with and without AF

The effect of AF stopped the model results from containing some unrealistic regional ethanol production (Fig. 10). Without AF (as indicated by the red lines), unrealistic spatially varying variations in ethanol production were observed relative to the with AF case (as indicated by the blue lines). For example, there were about 23 million liters of cellulosic ethanol production in Pacific Southwest (PSW) in 2025 but no production before or afterwards. Similar short-term variations were also observed for other regions such as Pacific Northwest- east of the Cascade Mountain (PNWE), Great Plains (GP) and Lake States (LS). Such a production pattern would not be likely in reality as it implies building then abandoning expensive facilities. Again ignoring AF upwardly biases cellulosic and crop ethanol production, leading to an over-optimistic prediction of market penetration.

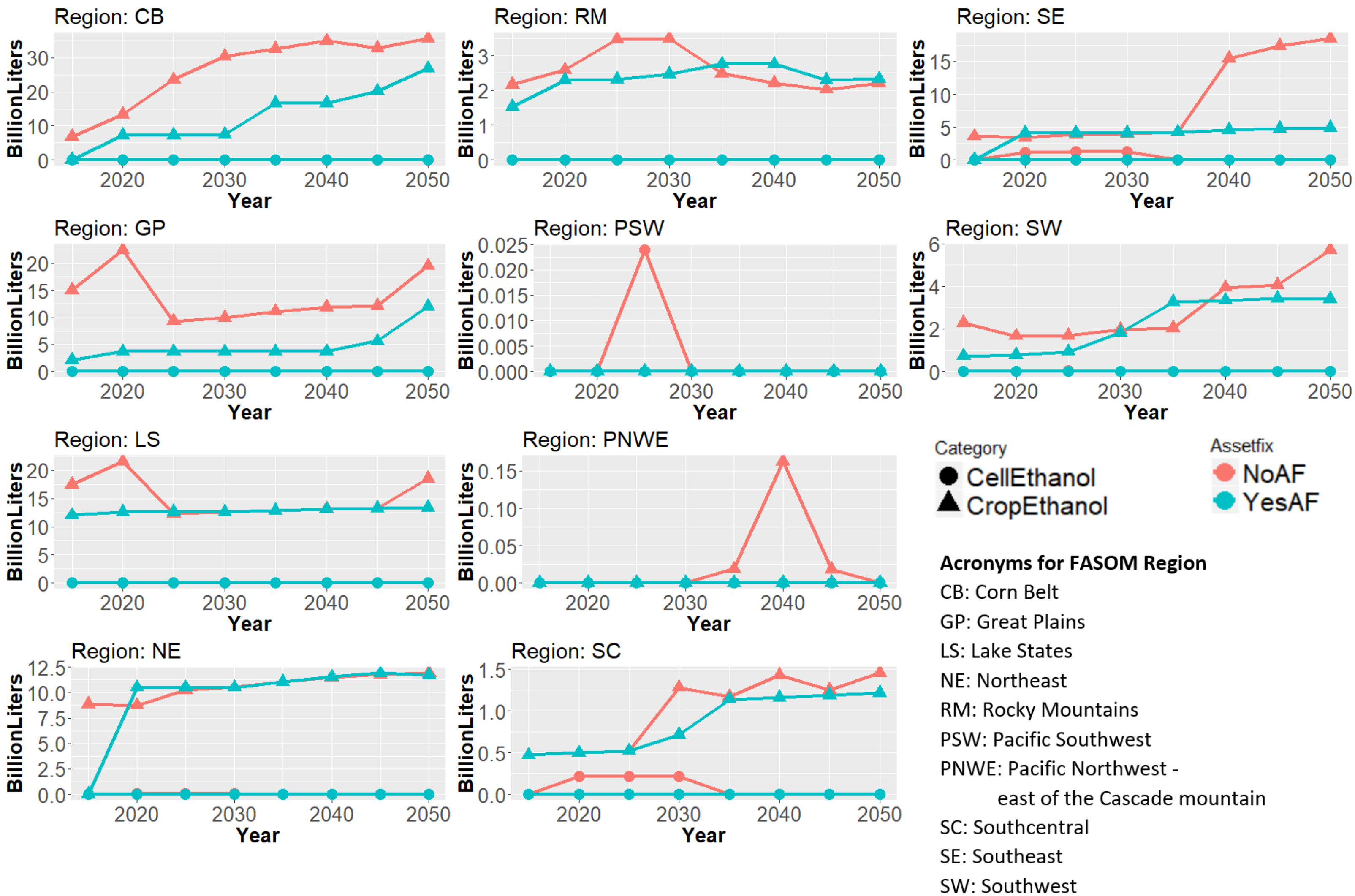
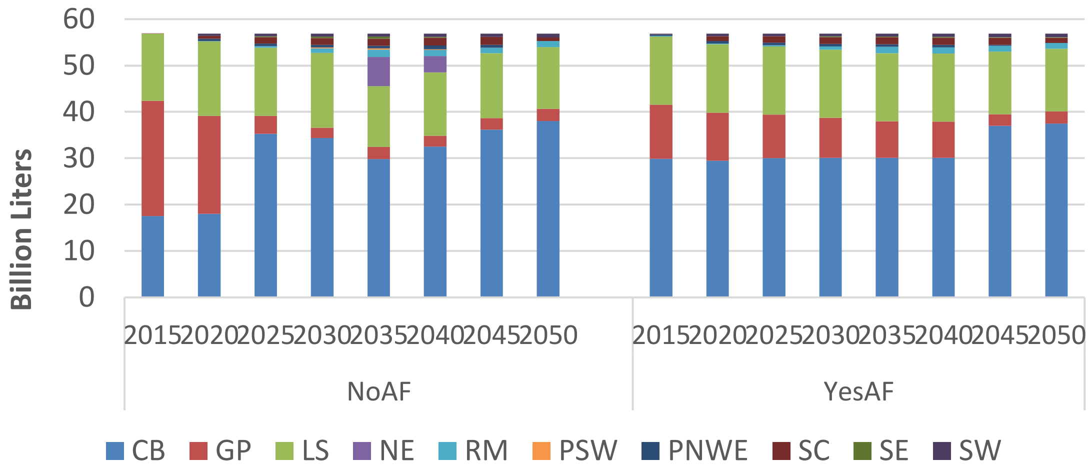


Figure 10. Ethanol production by region and feedstock in base scenarios with and without AF

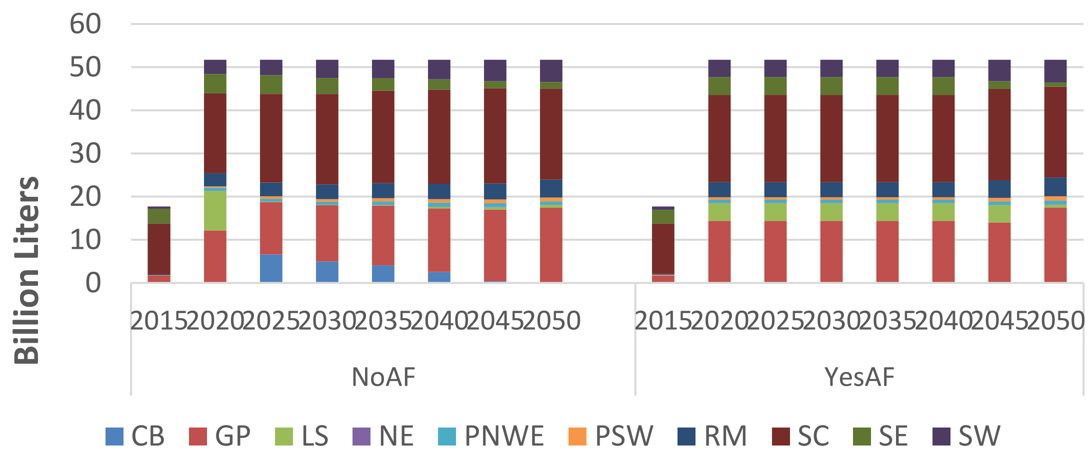
Meeting RFS2 Volumes with and without Asset Fixity

Fig. 11 shows ethanol production by region and type when producing the ultimate volumes contemplated in the RFS2 starting in the year 2020. As in the baseline scenarios, unrealistic, unstable production patterns were observed without AF. Illustrating this instability, about 8 billion liters of crop ethanol were produced in the Northeast (NE) in 2035 but this fell to to 4 billion by 2040 and disappeared completely by 2045 (Fig. 11a). Also, there was a more than 15 billion liters reduction in ethanol production in the Great Plains between 2015 and 2020 with it moving to the Corn Belt region in 2020. This also happened on the cellulosic side with the Lake States showing a high volume of about 10 billion liters in 2020 but then it falling to less than 1 billion is the subsequent years. No such dramatic changes were observed once AF was incorparted with the exception of Great Plains during 2040-2045. However, note that the capacity there remained in production for 30 years then dropped out so it was in line with the economic life assumption of 30 years. Similar consistency was also observed in the cellulosic ethanol case (see. Fig. 11b).

As mentioned in the scenario setup, for these runs the RFS2 mandate on cellulosic ethanol is incorprated in the model as a lower limit on production for the year 2020. The shadow price on that lower limit gives the cost estimate of meeting the level of the cellulosic ethanol volume contemplated by the RFS2. Such shadow price for the maximum level of the RFS2 mandate (the EISA volume targets for 2022) in year 2020 is \$0.43/liter (\$1.62/gallon) in the AF scenario. On the other hand, without AF the shadow price falls to $0.21/liter ($0.81/gallon). This indicates that neglecting the asset fixity concerns lead to a substantial underestimate of the cost of RFS2 implementation.



(a) Crop ethanol



(b) Cellulosic ethanol

Figure 11. Ethanol production by region and type in RFS2 scenarios with and without AF

Note: CB: Corn Belt; GP: Great Plains; LS: Lake States; NE: Northeast; RM: Rocky Mountains; PSW: Pacific Southwest; PNWE: Pacific Northwest - east of the Cascade mountain; SC: Southcentral; SE: Southeast; SW: Southwest.AF and cellulosic ethanol competitiveness

Fig. 12 shows the national levels of crop and cellulosic ethanol production for different price scenarios with and without AF, with the black bold line indicating the RFS2 target for cellulosic ethanol by 2022. Here we only see volumes approaching the level of the ultimate EISA mandates by 2025 if the price is $0.79 per liter or higher when AF presents. On the other hand, without asset fixity constraints the projected ethanol production is higher. Especially, an abrupt increase in cellulosic ethanol production is observed during 2040-2045 in the $0.79/liter scenario, indicating that once cellulosic ethanol production become profitable the production capacity increases by 80 billion liters in five years. Again, this is due to the lack of asset fixity constraints which is not realistic and not observed in the AF scenario.

A few more details are noteworthy. First, crop ethanol grows beyond today's levels as the price escalates over time in all cases but at low prices, we see no real penetration from cellulosic sources. However, as initial ethanol prices rise above $1.06/liter, then cellulosic ethanol becomes cost competitive surpassing the mandated 49-billion-liter level by 2025. This was consistent with existing pricing situation under RFS2. As of June 2017, the market wholesale price for gasoline is $0.41/liter and the cellulosic Renewable Identification Number price is $0.7/liter, placing the cellulosic ethanol production cost at $1/liter[4].

Second, let us examine the feedstocks used. On the first-generation side corn was the dominant feedstock. For cellulosic, agricultural residues, mainly corn stover, were

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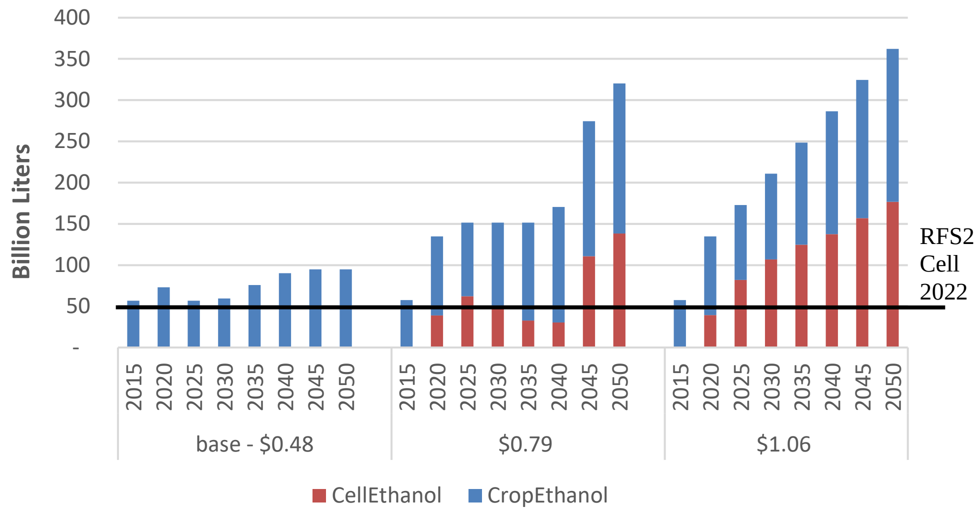
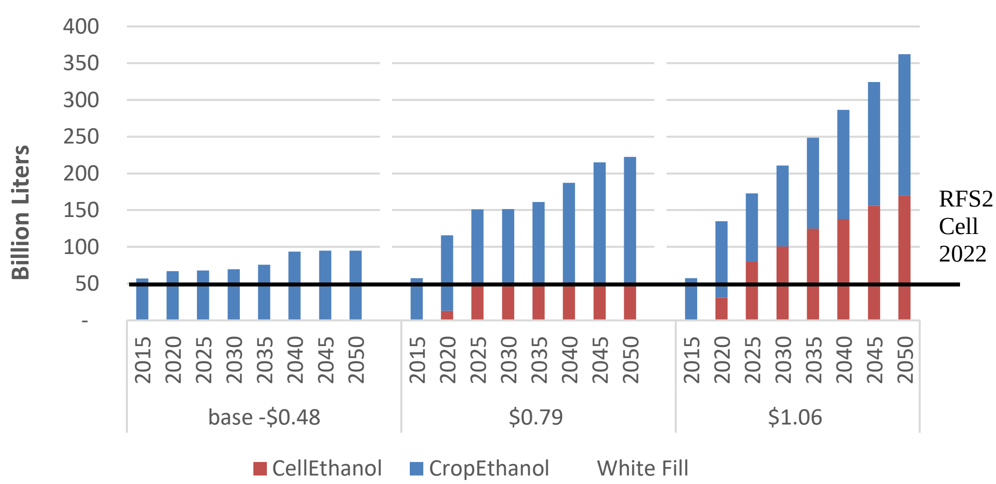
[4] We used the following approximation formula as suggested by Dr. Wallace E. Tyner: $P_{cell} = P_{gas} * 2/3 + RIN_{cell}$ where 2/3 adjusts the difference in energy content between gasoline and ethanol.

the dominant feedstock for cellulosic ethanol when prices were low. When ethanol price increased to $1.06/liter, a considerable amount of switchgrass based ethanol entered (see Fig. 13).

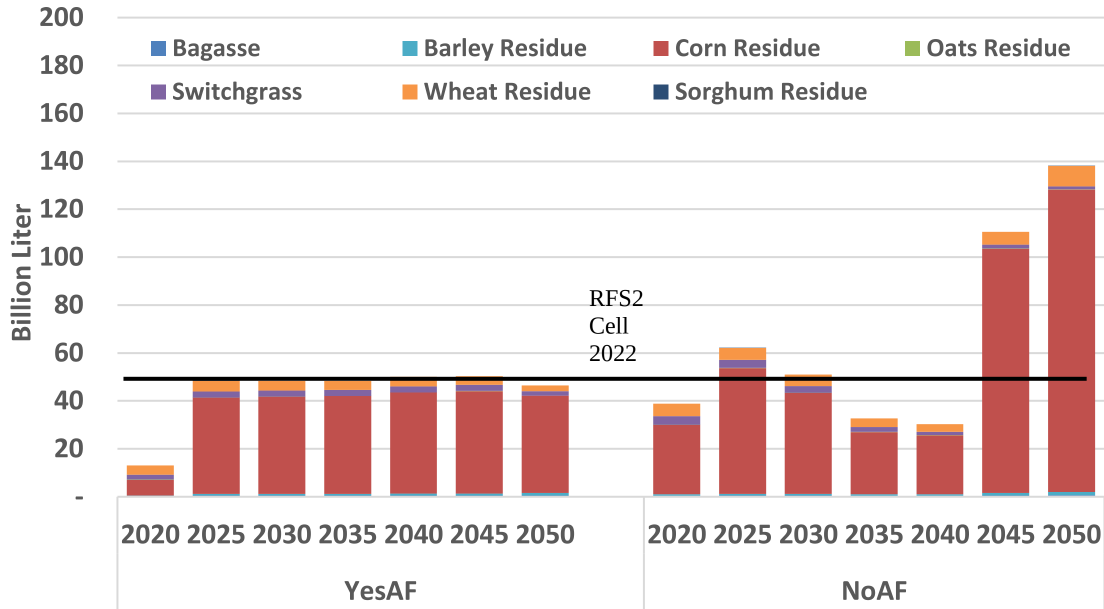


(a) Non-AF model

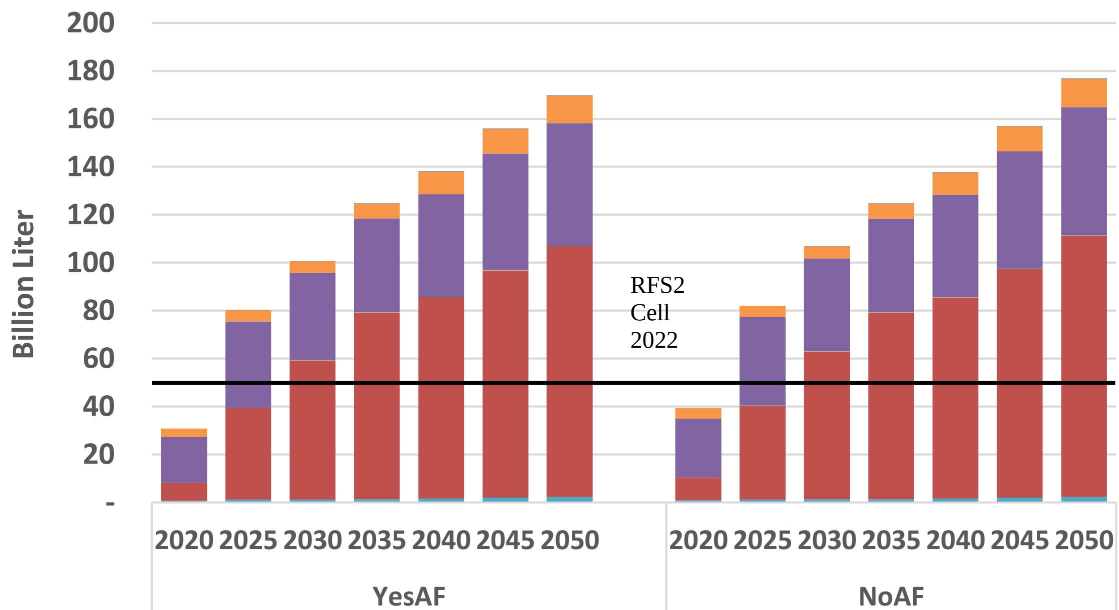


(b) AF Model

Figure 12. Ethanol production by price and type with and without AF



(a) Cellulosic Ethanol Production with price at $0.79/liter



(b) Cellulosic Ethanol Production with price at $1.06/liter

Figure 13. Cellulosic ethanol production by feedstock in the AF model

Concluding Comments

When a bioenergy plant is built, the corresponding capacity, processing technology and class of feedstock it can use are fixed in place and largely in operating characteristics until its retirement, which we call asset fixity herein. Our results unsurprisingly show neglecting asset fixity causes production location and capacity to jump around from region to region and feedstock to feedstock in adjacent 5-year periods. This permits production to move to whatever technology and feedstock combination which is the cheapest in that particular time period ignoring continuity of constructed facility location and processing characteristics. Also it allows costs to ratchet down over time as technological progress develops without considering the fact that once a facility is constructed that a substantial amount of the technology and cost structure is locked in. Running with and without such fixity shows a substantial increase in the cost of production when the model is not allowed to “cherry pick” without locking in location and technology. We also find that ignoring asset fixity could substantially reduce the long run estimates of the cost of cellulosic ethanol production. Specifically, ignoring asset fixity would nearly halve the estimated cost of RFS2 implementation.

This paper also examined the future economic competitiveness of cellulosic ethanol with different price projections with AF considered. The results showed that the minimal ethanol price to have free market ethanol production by 2022 at a volume approaching the EISA ethanol blending enabling legislation contemplated levels was about $1.06 per liter compared to the current ethanol price of about $0.48 per liter which is well in excess of the highest historical ethanol price was $0.68 per liter in 2006 (Nebraska Ethanol Board 2018).

CHAPTER IV

WILL THE MARKET LEAD TO A CLEAN ELECTRICITY FUTURE OR DO WE NEED POLICY SUPPORT: AN ECONOMIC ANALYSIS

Introduction

Electricity generation is the largest single source of carbon emissions in the US with estimated CO_2 emissions in 2016 amounting to 1.8 billion metric tons (MT) or about 35% of the US total (US EIA 2016b). Emissions from electricity generation vary by fuel with coal fired generation being the largest. In 2016 coal was used to fuel about 30% of the electricity generation but was the source of nearly 70% of the CO_2 emissions (see Fig. 14). On the other hand, renewable sources such as hydro, wind and solar do not emit substantial amounts of CO_2 during the electricity generation process[5].

External damages from CO_2 and other pollutant emissions are substantial and could be reduced if the generation mix shifted away from coal and other fossil fuel based approaches towards more renewables. The environmental and health benefits of replacing high-pollution fossil plants with renewable ones have been estimated to be between $14 to $170 per MWh (Buonocore et al. 2016). But, these costs are largely external to electric power generators' operations and as such the electrical generating firms have little incentive to do replacements other than those justified by reduced fuel, capital and operations costs.

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[5] Note wind and solar electricity still have life-cycle co2 emission consequences from manufacture, transport and installation of wind turbines or solar panels with small amounts involved in maintenance. For review, discussion and estimates see https://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_annex-iii.pdf.

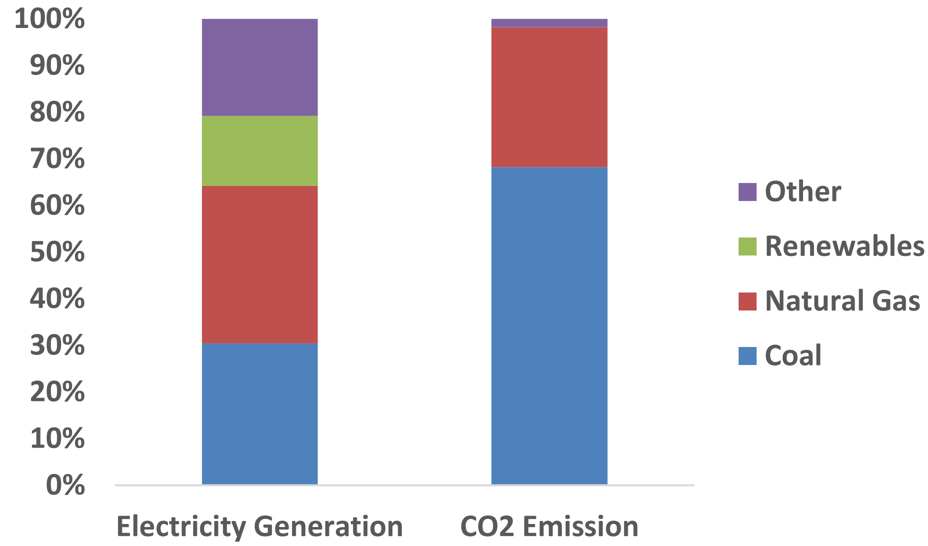

Figure 14. U.S. electricity generation and associated GHG emission in 2016

Until the last decade or so, the deployment of wind and solar was slow due to high generation costs relative to fossil fuel fired generation. However, costs have fallen dramatically in recent times and market share has accelerated, particularly for wind. Wiser et al. (2015) estimates wind based generation cost decreased by more than 90% between1980 and 2013 - from \$0.5/kWh to \$0.045/kWh. Lazard (2016a) estimates utility-level solar generation cost decreased by more than 85% between 2009 and 2015 - from \$0.35/kWh to \$0.055/kWh.

These cost reductions have stimulated expanded deployment. In the US, 27 gigawatts (GW) of new generation capacity was deployed in 2016 with almost a third (8.7 GW) based on wind and about 25% (7.7 GW) based on solar with the rest largely using natural gas. Meanwhile, the US retired 12 GW of older, mainly coal fired, plants (US EIA 2017c). As of December 2016, wind, solar and biomass accounted for 37.7%, 3.8% and 9.1% of total US renewable electricity and were the largest sources except for conventional hydropower (US EIA 2017b).

In addition to production costs and GHG considerations, renewable electricity generating capacity requires significant upfront investment costs that locks in future operating characteristics and locations (again an asset fixity effect as discussed in the previous essay). Furthermore, wind and solar generation are not as reliable being intermittent depending on weather and sunlight. Furthermore electrical energy is costly to store in large quantities making dispatchable electricity sources such as coal and natural gas more valuable. As a result, Denholm and Hand (2011) argue that significant enhancements in storage or management of intermittent sources are needed to achieve high levels of wind/solar market share.

Important questions going forward are: (1) Will we see a continuing large-scale market driven shift to renewable power? and (2) Can yet a larger-scale shift to renewables be achieved through policy support? Additionally, (3) if needed what form might policy support take among possible actions like direct R&D support to enhance technological progress, tax credits that reduce costs of production and investment, and/or carbon pricing of GHG net emissions or rewards to emission reductions. In this paper, we investigate the increase in market share of renewable generation under several key alternative assumptions regarding

- Differing future technological progress induced generation cost reductions,
- Increased prices for wind and solar power achieved through reliability enhancements via improved electricity storage and power system management,

- Possible carbon (GHG) emission pricing or reduction rewards.

In doing this we will also incorporate asset fixity for renewable installation as discussed in the previous essay. Analytically we will employ rural sector modeling depicting agriculture and rural electricity generation powered by biomass feedstocks, wind and solar. We also examine the resulting environmental consequences, especially for CO_2 and other greenhouse gas emissions.

The study results indicate significant continued growth in renewables reaching 25% market share by 2050 even without policy support. This shift results in a net GHG emissions reduction of 72 MT of CO_2e annually. We also find that the renewable market share could be significantly increased with enhanced technological progress in wind and solar generation cost, with the penetration reaching 31% by 2050. We also find an even greater market share (67% by 2050) could be achieved under a carbon pricing directed toward emission reductions, or via less of a price discount for the intermittent sources achieved through improvements in energy storage and/or power system management. On the other hand, with low technological progress on wind and solar electricity, a lack of improved energy storage or GHG policy, renewables only achieve a 13% share by 2050.

Background: Renewable Market Projection Literature

Many studies have projected the future renewable electricity market share from an engineering perspective examining cost, system stability and environmental impacts. For example, Bloom et al. (2016) and GE Energy (2010) examined the implications of a 30-35% electricity market share in Eastern and Western US, respectively by 2020. They found that at such levels of market share no extensive infrastructure investment was needed, significant fuel cost could be saved and carbon emissions were also reduced. However, increasing market share of wind and solar did lead to higher operating cost and needs for additional attention in case of sudden supply shortfalls. Also Hand et al. (2012) examined an 80% US renewable electricity market share by 2050. The study showed that infrastructure investment was needed to achieve this level of renewable market share and that a diverse generation portfolio was preferred to reliance on a single source.

Several other studies have examined achieving 100% renewable energy including both electricity generation and other sectors such as transportation. Jacobson (2015) examined 100% renewable energy in the US while Jacobson et al. (2017), Connolly et al. (2016), and Mathiesen et al. (2011) also looked at achieving this globally. These studies included the electrification of other energy sectors (especially transportation) to achieve carbon reduction targets and suggested using carbon pricing policies to offset the increase in production cost from 100% renewable market share. While these studies provided valuable insights on the technical frontier there are significant economic, political and other realistic constraints that make made such levels hard to realize. Clack et al. (2017) was critical of the Jacobson et al. (2015) and emphasized that a transition towards a 100% renewable future would require an large infrastructure investment in energy storage/conversion systems, which they claimed was omitted in Jacobson et al. (2015) leading to an overly-optimistic cost estimates.

A few studies have examined the future renewable market share rate allowing the rate to be determined by market forces. One example is the Annual Energy Outlook

(AEO) by the Energy Information Administration (EIA) which provides a long-term forecast using the National Energy Modeling System (NEMS). AEO also provides a forecast under scenarios with varying economic, and fossil fuel price and fuel availability conditions. Details on the AEO analysis is available at EIA (2017a). However, since AEO generally focuses on the entire US energy sector and top-level political and/or socioeconomic conditions, its spatial resolution on renewable electricity is relatively coarse and the sensitivity analysis within AEO scenarios do not provide enough flexibility reflecting variations related to the intermittent nature of wind and solar, or alternative technology progress rates as we would here. More specifically the analysis herein will forecast market driven increase in share of renewable electricity and how it changes under varying production cost, energy storage or carbon price conditions for renewable electricity production.

Methodology

To carry out this study we use a spatially disaggregated model that gives regional potential supplies of agricultural biomass feedstocks along with potential wind and solar capacity and cost. The model also has dynamic features depicting evolving demand over time, plant obsolescence, facility construction, asset fixity and subsequent operation.

To undertake this study, we expand upon the multi-period Forestry and Agriculture Sector Optimization Model (FASOM) (Adams et al. 2005; Beach and McCarl 2010). FASOM is a widely-used sector model that has been applied in studying agricultural, climate change, GHG emission and bioenergy issues. In the energy arena it has been used to analyze agricultural and forestry products as feedstocks for bioelectricity and biofuels looking at market implications, competitiveness and GHG emission effects (McCarl et al. 2000; Murray, Sohngen and Ross 2007; Beach and McCarl 2010). For this study, we expand FASOM to include wind and solar based electricity generation.

Adding Wind and Solar to FASOM

We add wind and solar location-specific capacity and cost information to FASOM reflecting a cost volume relationship, capacity and functional life of facilities. The specification is based largely on two NREL data sources: 1) the Regional Energy Deployment System (ReEDS) model and 2) the 2016 Annual Technology Baseline (ATB). ReEDS is a long-term, capacity expansion, spatial model for continental US (see details in Eurek et al. (2016)). For this study, ReEDS provides the spatially heterogeneous capacity data for both wind and solar. Notably, ReEDS categorizes renewable sources into different resource classes based on their quality (namely speed for wind and radiation for solar). ReEDS also provides the grid interconnection cost for potential newly-added capacities since it varies by region depending on location and local power system characteristics. ReEDS divides continental US into 356 regions for wind data and 154 regions for solar data.

The ATB is a set of energy technology input assumptions maintained by NREL for energy modeling. It also contains a diverse set of potential future scenarios depending on the rate of technology progress rates (e.g. high-, mid- and low-cost scenarios). See details about ATB from Hand and Kurup (2016). In this study, ATB provides production cost data (covering construction, maintenance and operation cost) for wind and solar electricity which is location-free conditional on given resource class.

Regional generation costs and capacity

Including the ReEDS data into FASOM requires dealing with the differing spatial resolutions. Particularly, FASOM has 11 aggregate market regions along with biomass feedstock production in 63 regions[6]. To include the more spatially disaggregate data from ReEDS, we represent a multi-step, escalating cost, supply curve of wind and solar possibilities within each FASOM region. This is done by sorting the ReEDS data in each FASOM region by generation cost from the cheapest to the most expensive then entering this as a series of alternative steps limited by capacity. In turn, the model solution will walk up the generation cost curve until the marginal cost matches the cost of generation via conventional fossil fuel sources considering fossil operation and possibly carbon prices. Detailed discussion on this procedure is in Appendix 1.

Maximum rate of market share – demand quantity

Another model feature involves the rate at which renewables can penetrate the market. We set the maximum rate of increase in market share for renewable electricity equaling to the projected electricity demand growth rate plus retirement in existing generation plants reaching the end of their economic life. Specifically, we assume the annual electricity demand growth rate is 0.77% based on US EIA (2016a) and that

[6] FASOM divides the contiguous U.S. into 63 regions for agricultural production and 11 regions for secondary good processing (i.e. making ethanol and diary product).

existing coal and natural gas plants are retired once they reach 40 years old based on ATB 2016.

Renewable infrastructure investment

Based on ATB 2016 estimates, we assume that wind and solar capacity lasts 20 years and biomass 25 years. The renewable plants once constructed are treated as an immobile asset fixed in place for their economic life. We also assign up-front fixed cost of deploying the wind and solar all in the year of construction. We then include in FASOM a facility operation variable which reflects generation limited by constructed capacity incurring variable costs.

Wind and solar reliability discount

Intermittent sources like solar and wind power have different reliability characteristics relative to power generation fueled by coal and natural gas. To insure reliability under current conditions backup power plants (usually based on fossil fuels) are needed to ensure power system stability, which results in higher cost (Hirth 2013). To reflect this, we follow Hirth (2013) and include price discounts for wind and solar generation that grow as market share increases (Fig. 15). For example, when the market share of wind electricity reaches 10 percent, a 16% discount is applied to the price of wind electricity, suggesting that wind electricity needs to be cheaper to be competitive (more details on the price discount specification appears in Appendix 3).

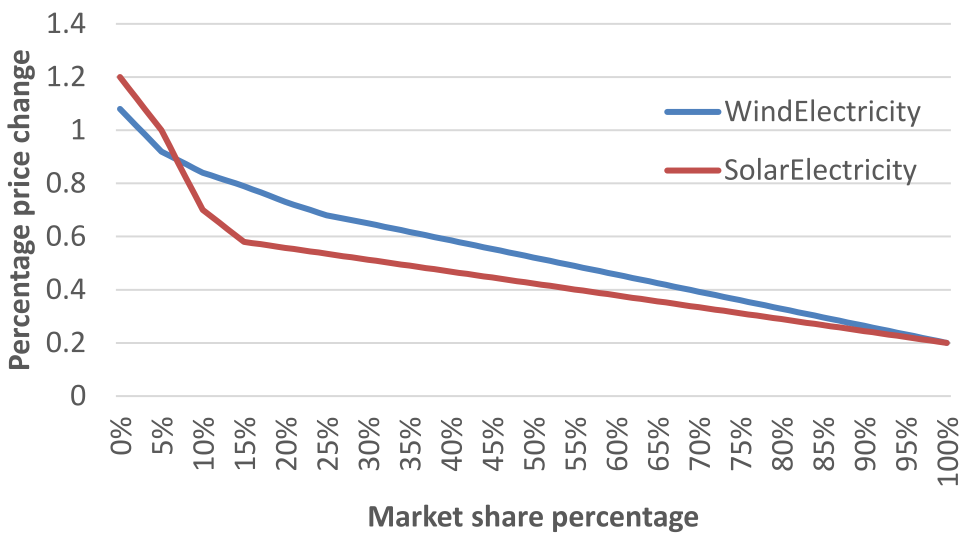

Figure 15. Price discount premium as market share increases for wind and solar

Tax Credits

In representing costs of facility construction, we consider the Investment Tax Credit (ITC) that following DOE documents (US Congress 2011), which is a 30% tax rebate for solar investment starting in 2015 phasing down to 10% by 2020 and then remaining at 10% from then on. Similarly, the assumed ITC for wind is 10% in 2015 phasing down to 0% in 2020 and thereafter.

GHG emissions

We also compute GHG emission reductions with a shift in electricity generation towards renewable energy. This is done assuming that renewables displace construction of new natural gas based generation. Currently, new generation plants are mostly natural gas or renewable plants (US EIA 2017c). Thus, when a new renewable plant is constructed we credit GHG savings as the amount estimated by life-cycle GHG accounting over natural gas minus that for the renewable source chosen. For wind and solar we use the average offset computed across the studies by IPCC (Bruckner et al. 2014) and NREL (Lifset 2012) as in Fig. 16. The resultant GHG emission offset from an additional kWh of wind and solar electricity production is 457 and 422 grams CO_2e, respectively. Emission accounting for biomass electricity follows the procedures in McCarl et. al (2000) where the GHG offset is still calculated from the amount of natural gas electricity replaced but the emissions vary by feedstock accounting for different farm management practices, feedstock heating value, etc. and is endogenously computed in FASOM.

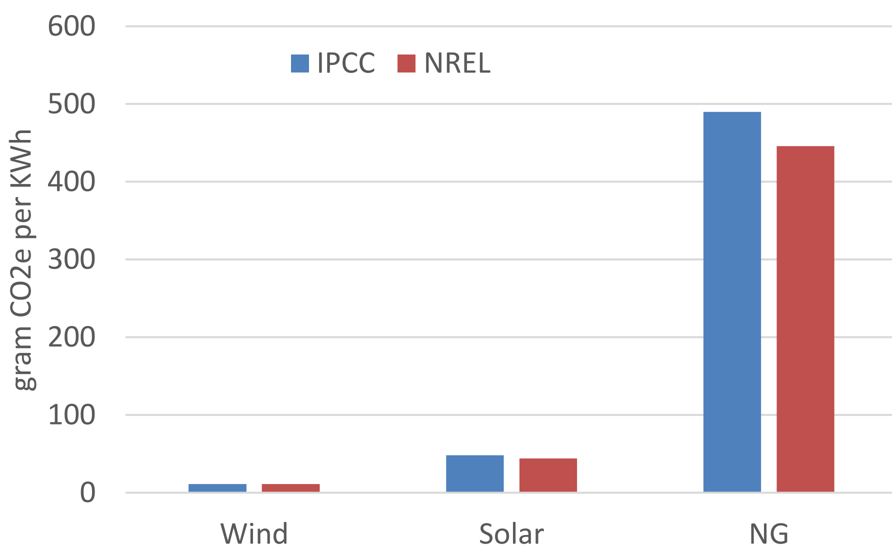

Figure 16. Comparing life-cycle GHG emissions from wind, solar and natural gas electricity estimated by the IPCC and NREL

Prices for Electricity

We assume that new renewable electricity producers are price-takers in the market and face a price for generated electricity that equals the levelized cost of electricity (LCOE) generated from natural gas fired generation as the backstop price less any price discount for intermittency. This backstop price is increased by the external social cost when carbon pricing is simulated. This results in new investment in renewable electricity capacity only when the cost is at or below the backstop price (less any discounts). The LCOE of natural gas electricity we used was drawn from ATB 2016 ($67/MWh).

Technology Progress Production Cost Assumptions

Technological progress has been crucial to the recent increase in market share and relative cost of wind and solar electricity. This will undoubtedly remain so for the near future as the ATB 2016 projects further cost declines and efficiency gains. In this study, we will adopt the mid-cost scenario from ATB 2016 for wind and solar cost projection over time. For biomass based generation we do not assume progress in combustion efficiency but do assume gains in yield per acre which in turn lowers hauling and farm production cost. More details on the technical progress assumptions are given in Table 6 and Fig. A4.

Table 6. Assumptions on technical progress over time

Resource Type	Technical Progress Assumptions
Wind	(1) Capacity factor* of wind farms increases by 9-13% from 2015 by 2050 depending on regional characteristics. (2) Capital cost decreases in most regions (by $48-$212/kW depending on region). Increases in capital and or operating cost is observed in regions with less desirable conditions (i.e. projected capacity factor less than 30%).
Solar	(1) Capital cost of installing capacity decreases from $1898/kW in 2015 to $823/kW in 2050 for all regions (56%).
Biomass	(1) No progress in electrical generation per ton of feedstock. (2) Assumes biomass yield increases over time based on historical observed rate of increase in sorghum yields by region. This reduces hauling and feedstock production cost per ton.

* The capacity factor is the unitless ratio of an actual electrical energy output over a given period of time to the maximum possible electrical energy output over the same amount of time. Nuclear plants generally have the highest capacity factor (around 90%) while wind farms are much lower (average 36.1% for existing wind farms) and is increasing with more efficient wind turbine design.

FASOM Baseline Results

The initial analysis involved runs under the base technology assumptions above. Fig. 17 shows the consequent increase of renewable electricity market share by source. Here we see substantial market share by renewables with market share rising from 6% in 2015 to 25% in 2050 (1.25 billion MWh). Wind generation is the leading renewable source deployed and rises from a 4% share in 2015 to 14% by 2050. Solar starts at about 0.5% in 2015 and rises to about 6% by 2030 and stays relatively constant thereafter.

Biomass electricity starts at 1% then rises to about 5% by 2050. The growth in renewables projected here is a result of continued technological progress projections which would involve continuing tax credits and current publicly supported wind and solar R&D such as the ITC. These results show that significant expansion is likely to occur even without additional policy support.

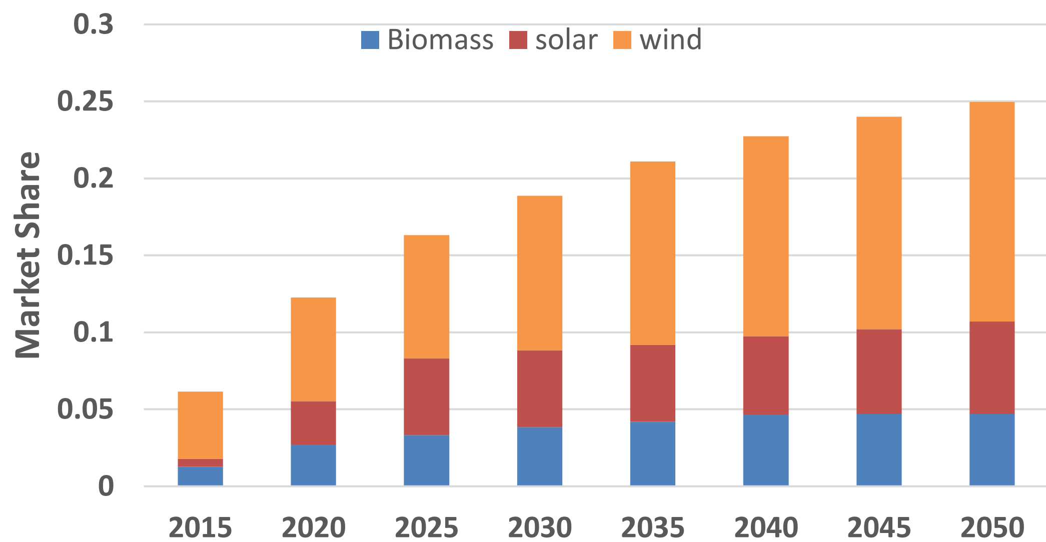

Figure 17. Projected renewable generation by source in baseline

The pattern of renewable deployment varies spatially (Fig. 18). Wind generation first appears in the Great Plains and Northern Texas where the cheapest wind power is available. Then wind deployment gradually spreads throughout the central US, (mainly in the Great Plains. Solar deployment is more concentrated, with almost all solar plants in the Southwest and California. The amount of biomass capacity built is by far the smallest with it mainly occurring in the Southeast in areas suitable for switchgrass.

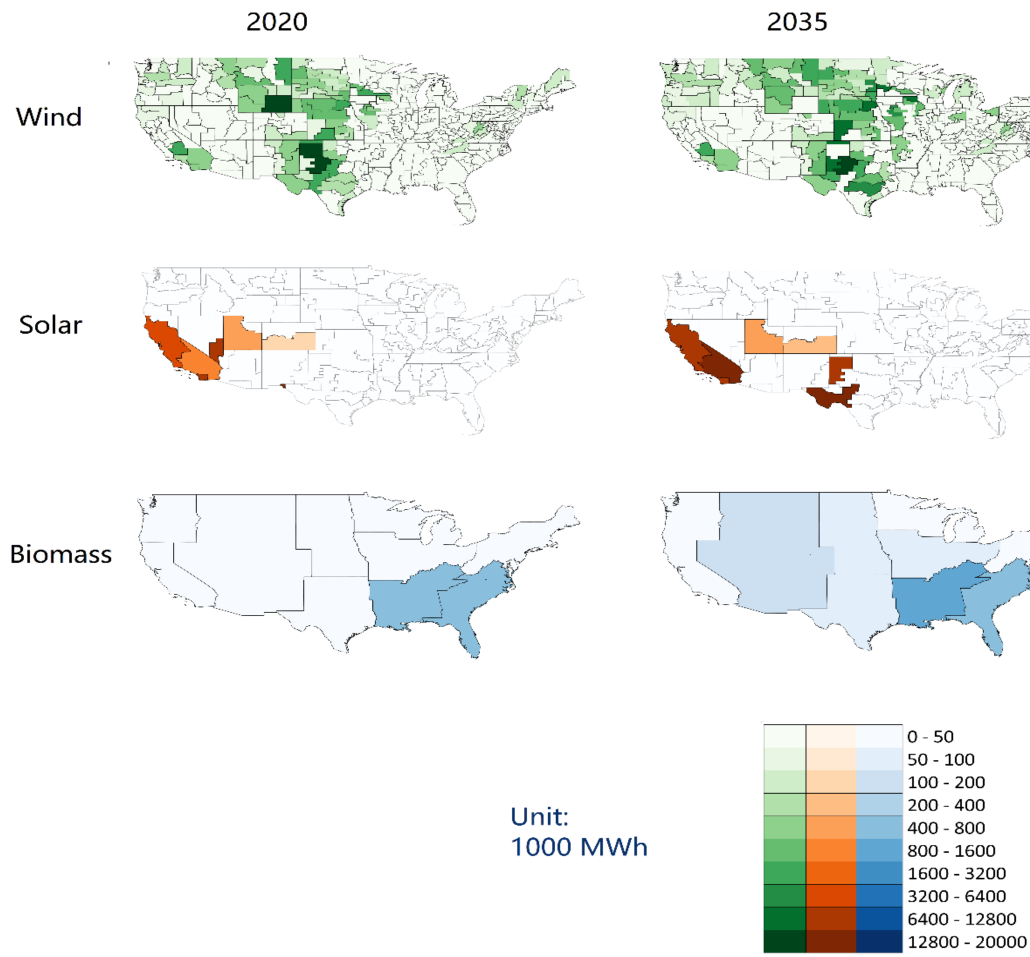

Figure 18. Renewable generation distribution in baseline scenario

Model Validation

We can partially validate the model by comparing baseline results with observed market share of renewable electricity. Fig. 19 shows the FASOM projected renewable generation during 2015-2019 versus real-world data for 2013-2016 available from US EIA (US EIA 2017b). The predictions of the model are close to the reported data in magnitude but generally smaller and it is likely due to our omission of local policy incentives (such as the State Renewable Portfolios).

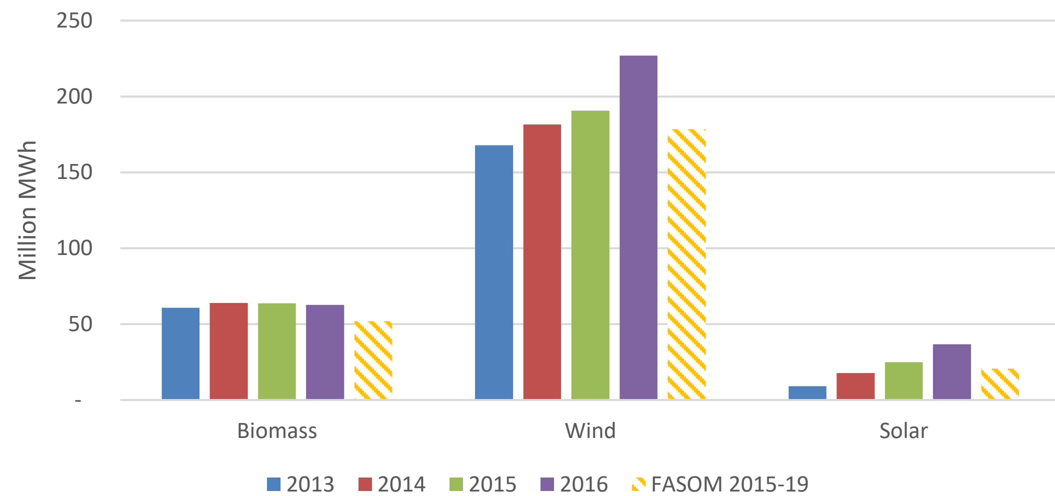

Figure 19. Projected generation for FASOM baseline 2015-2019 versus real-world production

Note: The solid bars are real-world data and dash bars are from FASOM projection

It is also worth comparing the FASOM projections to Department of Energy projections (US EIA 2017a). Fig. 20 shows the comparison between FASOM and the 2017 AEO projection (AEO2017) which reveals similar patterns for wind and solar but that FASOM expands biomass-based generation at a faster rate. One potential driver behind the high biomass prediction is the wind and solar price discounting with increased market share which according to Mai et al. (2012) is a major factor in determining the future role for biomass based generation. Moreover, though FASOM predicts higher renewable production in the long term than AEO2017, this is less worrisome considering AEO tends to be conservative in its renewable electricity forecasting (US EIA 2016c).

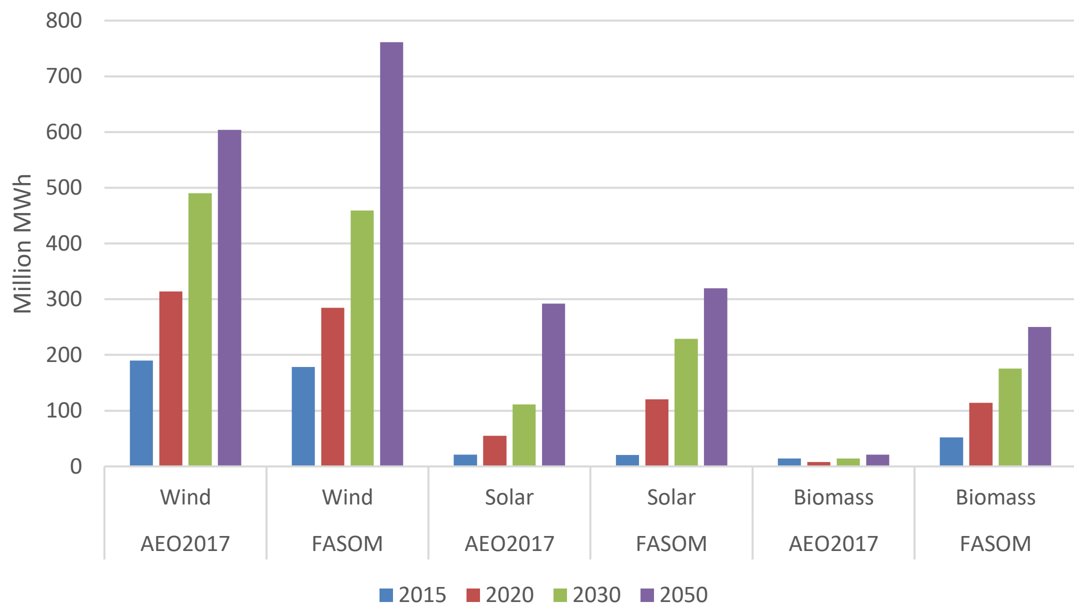

Figure 20. Projected renewables generation in FASOM baseline versus AEO case, 2015-2050

Overall, we feel the model projections appropriately show comparable trends with real-world data and AEO projections and is thus suitable for use in studying the issue of policy support.

Policy Support Analysis

Given GHG emissions and other externality costs involved with fossil fuel based electric generation it may be socially desirable to encourage a greater renewable generation share through policy. Possible directions involve subsidies or requirements intended to increase market share such as 1) enhancing technical progress in wind and solar cost reduction, and 2) enhancing technical progress in wind and solar reliability via improved storage or operations, 3) mandating increased deployment, and 4) rewarding lower GHG emission rates. Here we examine changes in renewable market share relative to such possible directions.

Technological Progress on Production Cost

A key factor in past and future market share of renewable electricity involves the degree to which solar and wind costs will drop. In the baseline, we used the mid-cost projection from ATB 2016 for wind and solar along with an assumption about growth in biomass feedstock yield per acre (see section 3.3 for details). For the sensitivity analysis here we included two additional scenarios (High-Tech and Low-Tech) based on the low- and high-cost ATB 2016 scenarios reflecting greater or lesser policy based incentives for direct investments in technological progress. Specifically, we have the following mapping:

- Baseline: Mid-cost, ATB 2016
- High-Tech: Low-cost, ATB 2016
- Low-Tech: High-cost, ATB 2016

Details on the high- and low-cost ATB scenarios and how they are different from the mid-cost scenario is given in Appendix 2.

Fig. 21 presents the results under these three scenarios. Under high technological progress, market share of renewables is larger than under the base with 2050 with the wind generation market share increasing from 14% to 18% and solar market share increasing from 6% to 10%. On the other hand, under the low technological progress future the market share falls substantially with renewable electricity only having a 13% share in 2050 total as compared to 24% in the baseline. We also see a minimal role for solar. Thus, if a policy goal is to have larger shares of renewables the incentives for technological progress on wind and solar generation R&D may need to be maintained or enhanced.

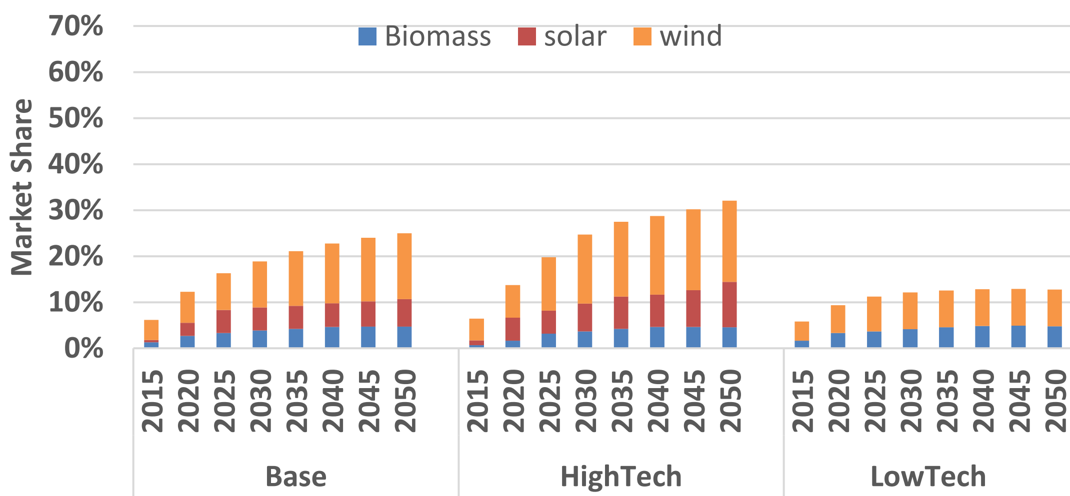

Figure 21. Projected renewables market share under alternative cost reduction scenarios

Renewable Price Discounts Results

Next, we examined the impact of reducing the renewable price discount arising from potential improvement in electronic energy storage or power system management. Policy could reduce such price discounts in two ways. First, there could be accelerated investment in or direct development of cheap, large-scale energy storage methods

(Beaudin et al. 2010). This could also involve development of a vehicle-to-grid storage system (Hodge et al. 2010). Second, improved wind/solar power forecasting (Martinez-Anido et al. 2016) or improved scheduling and inter-connection could lower the cost of managing intermittent generation.

To represent these technological perspectives, we considered two alternative scenarios:

- **No Discount:** 0% price discount for wind and solar based electricity assuming extreme storage improvement
- **Half Discount**: 50% of the discount assuming moderate storage improvement.

The results are shown in Fig. 22. Reduction in the price discounts has a major influence on renewable market share when the price discounts are cut in half, especially for wind. Under the case with no price discount, there is a substantial increase in 2050 projected wind and solar market share with the total share rising above 60%. On the other hand, biomass electricity is almost eliminated by 2050. This indicates that improvement in energy storage or related improvement in power system management will greatly increase wind and solar competitiveness as also argued by Hirth (2013), suggesting policy incentives or direct R&D efforts in that area would likely have a major influence on market share.

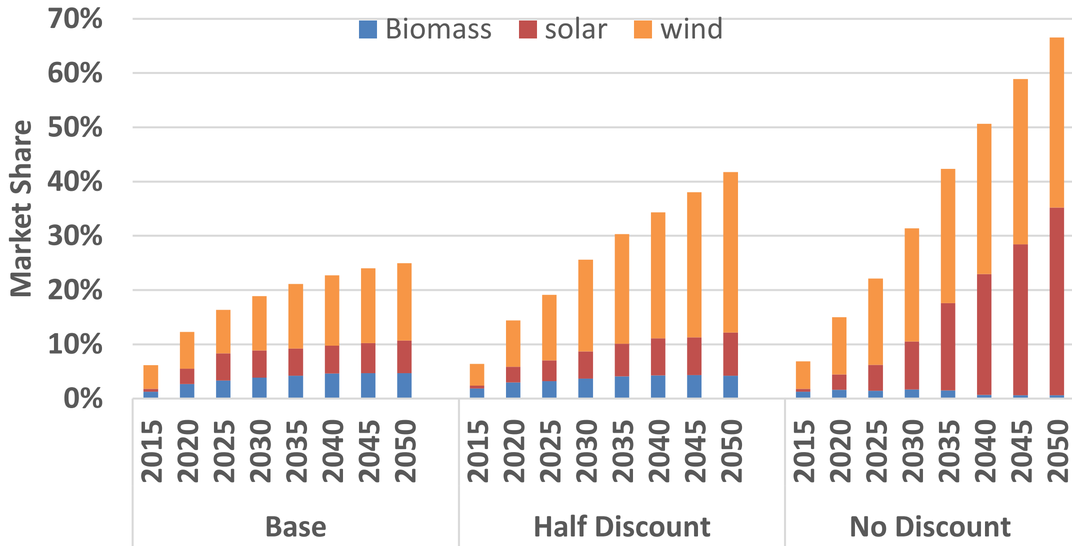

Figure 22. Projected renewables market share under alternative energy storage scenarios

Effects of Carbon Pricing

Another possible policy direction involves valuation of the environmental benefit of GHG emission reductions when employing renewable electricity (Baker III et al. 2017; McCarl and Schneider 2000). This could involve imposition of some sort of a limit on emissions with an associated trading market like might have happened under the now inactive Clean Power Plan or imposition of a form of a carbon tax. Via either mechanism carbon emission reductions would have some value and we simulate this through the use of a carbon price. In forming these scenarios we used **Low CO_2** and **high CO_2** price scenarios based on those developed by the US Federal Government Interagency Working Group on the Social Cost of Greenhouse Gases (2016) as reproduced in Table 7.

Table 7. Social cost of CO2, 2015-2050 ($/MT) adopted from US Federal Government Interagency Working Group

Year	Low	High
2015	$11	$36
2020	$12	$42
2025	$14	$46
2030	$16	$50
2035	$18	$55
2040	$21	$60
2045	$23	$64
2050	$26	$69
Discount rate	5%	3%

The market share results for alternative carbon prices are in Fig. 23. Not surprisingly, the results show carbon prices bring about significant increases in renewable market share compared to the baseline case. Generally, across the scenarios we see wind exhibits the largest gains while at low carbon prices biomass generated electricity is second and solar third. However, as the carbon prices rise then solar becomes the second most favored and biomass share becomes smaller. Across these assumptions, the market share of total renewables increases to roughly 40% under the lower carbon price scenarios and 62% under the higher carbon price.

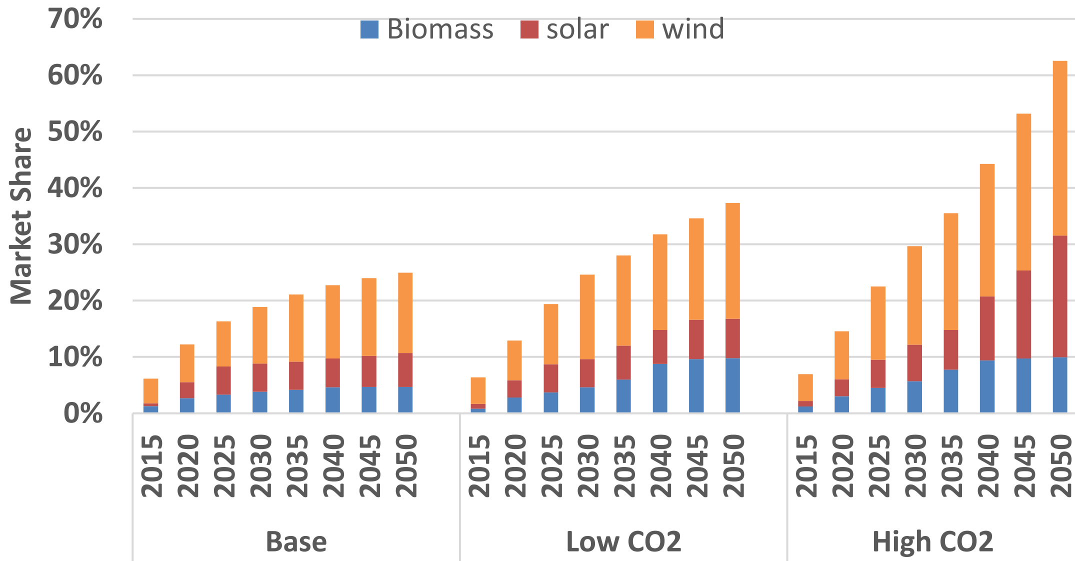

Figure 23. Projected renewables market share under alternative CO2 price scenarios

Joint Scenarios

Additional scenarios were also run jointly reflecting altered technological progress along with carbon prices. These results indicate show that carbon price can help overcome slower technological progress (see Appendix 4).

GHG Emission Reductions

One additional question examined by this study is the effects on greenhouse gas emissions. Increasing the market share of renewables has significant GHG benefits. Fig. 24 shows the changes in GHG emission benefit for alternative policy scenarios compared with the baseline, which is linked directly to quantity of renewable electricity produced. In the High-tech scenario, an additional 17 million CO_2e MT of GHG is reduced due to expanded wind and solar electricity generation compared with the baseline scenario while the Low-tech scenario leads to extra 28 million CO_2e MT of emissions. The incorporation CO_2 price at $11 and $36 per MT would lead to an additional GHG emission offset of 26 and 78 million MT respectively. Wind is the largest contributor due to its better life-cycle emission performance. We also note that, in two scenarios with reduced price discounts, there is increase in GHG benefit from wind and solar electricity but slight decrease from biomass. No significant changes are observed in the agricultural sector or from biofuel production.

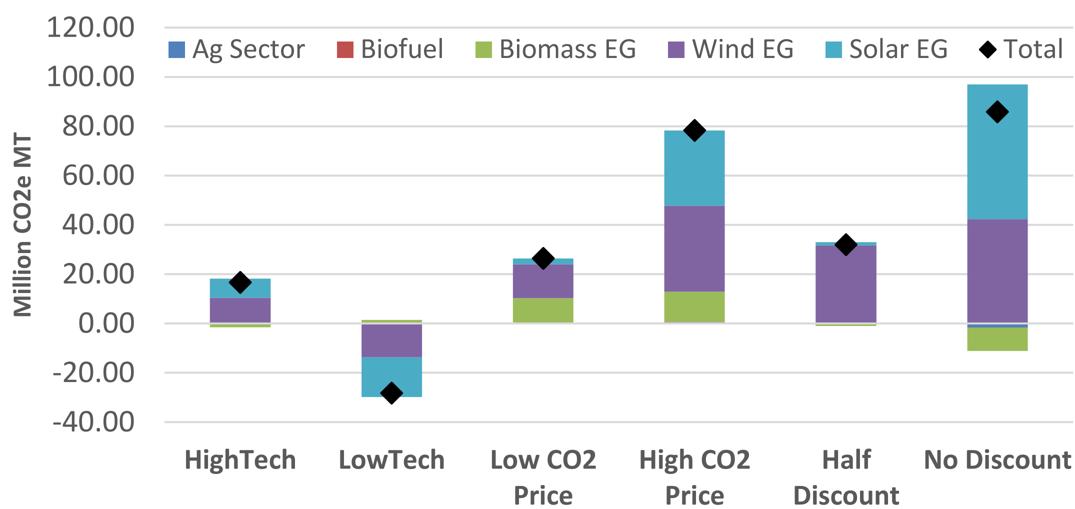

Figure 24. Annualized benefit in GHG emission reductions compared with baseline, 2015-2050

Discussion and Conclusion

Our study examines how changes in the technology and possible policy forces increase the share of renewable electricity in the power system and accompanying reductions in GHG emissions. Several findings emerge.

First if currently observed rates of technical progress persist then we project wind and solar will achieve a 25% share by 2050 with an accompanying emission reduction of 72 million MT of CO_2e annually or about 4% of today's GHG emission from US electricity sector. The magnitude of this market share basically matches the projection in the EIA Annual Energy Outlook.

Second, if additional penetration is desired several developments would push beyond a 25% share for renewable electricity generation. One development involves accelerated technical progress. In particular, on average a 20% reduction in wind and 45% reduction in solar electricity production cost led to a projected renewable market share of 31%. We also note a reduction in technical progress rate could render an almost stagnant share compared to today so a continued R&D role would appear to be beneficial and perhaps essential. Another direction involves enhanced development of storage or operating means to improve solar and wind reliability in turn reducing price discounts. Such a development in the form of a halving of the price discount pushes market share up to 42%. Finally, rewarding greenhouse gas emission reductions also increased market share substantially with it rising to nearly 37% with CO_2 at $11/MT and 62% at $36/MT.

Overall we find a substantial increase in market share if technological development proceeds at anticipated pace but that the share can be more than doubled under reliability increasing (battery storage) technological developments or the rewarding of GHG emission reductions.

CHAPTER V

CONCLUSIONS

Society faces major interrelated challenges in maintaining food and energy security as well as in addressing climate change. This dissertation reports the results of analyses pertaining to issues involving agriculture, renewable energy and climate change. Specifically, in a US setting, the following items are addressed:

- The effects of climate change on crop productivity;
- The economic competitiveness of cellulosic ethanol;
- Electricity market penetration and how it changes under alternative potential technology, reliability and carbon pricing developments.

Chapter II (the first essay) deals with econometric estimation of climate impacts on corn yields in the US Corn Belt. Specifically, we address ways of reducing problems raised by omitted, regionally correlated variables via application of a model that considers regional correlation in omitted variables. In particular, the Spatial Durbin Model is applied to a corn yield panel data set in the geographic region of the Corn Belt states. This model specification, which has not been previously used in such a setting, assumes the model residuals contain spatial patterns rather than being idiosyncratic, and also allows the residuals to be correlated with the independent variables. After estimation out-of-sample goodness of fit statistics indicate that the spatial model outperforms non-spatial, conventional panel models, especially in extreme drought years although the difference in the coefficient estimates is fairly small. Also, the study results show an inverse-U shaped relationship between temperature and yield with low and high temperatures causing substantial declines as has been found in a number of previous studies.

Chapter III (the second essay) reports on an investigation of the projected market penetration of cellulosic ethanol with and without consideration of asset fixity. Namely, whether or not a market share analysis considers or neglects the fact that bio-refineries once built become fixed assets in a particular location, requiring particular types of feedstock and contain a fixed, somewhat inflexible technology. In doing the study optional asset fixity characteristics for biorefineries are added into the FASOM model which is run with and without those features. Results show that omission of asset fixity overstates market penetration substantially yielding unrealistic production patterns with biorefineries jumping around from region to region and feedstock to feedstock in adjacent 5-year periods as the model exploits low cost situations. In terms of market penetration, the model with and without asset fixity is used to investigate cellulosic ethanol market penetration under alternative ethanol prices in the absence of mandates. The results show that with asset fixity cellulosic ethanol production does not rise to the levels contemplated in the Energy Independence and Security Act until the ethanol price is at or above $1.06 per liter ($4 per gallon) which considering energy equivalence corresponds to $1.59 per liter ($6 per gallon) of gasoline. To put this into context, this is 56% higher than the highest observed ethanol price in history ($0.68 per liter in 2006).

Chapter IV (the third essay) presents results from an examination of the US renewable electricity future. Specifically, the market penetration of wind, solar and biomass based electrical generation is investigated under current projections of technological progress and alternative market conditions. To do this the FASOM model is augmented to include wind and solar based electricity generation. The results indicate that if currently observed rates of technical progress persist, that renewable electricity will achieve about a 25% share of the electricity by 2050, which is consistent with AEO projections. We then investigate market penetration sensitivity to (1) future reductions in wind and solar generation costs, (2) reductions in price discounts facing renewable electricity due to increases in reliability, and (3) carbon pricing of greenhouse gas offsets. We find each of these developments significantly increase future market share, with developments in reliability (through perhaps cheaper, more capable batteries) and carbon pricing showing potential of achieving more than a 60% market share by 2050.

Naturally, this work is subject to a number of limitations some of which raise possible future research directions. In Chapter II, the use of spatial models mitigates but does not eliminate omitted variable bias and a Monte Carlo study might be done to see how successful it is. Also, our model assumes a stationary relationship between the included and omitted variables, and stationary spatial correlations between regions. Such an assumption might not hold in the long-term as climate change might change joint distributions and correlations. In the other words, climate change might not only change crop yields but also their spatial correlation over time. More flexibility could be added to the model using perhaps hierarchical modeling (Gelman 2006) and allowing the spatial correlations to vary over time. Perhaps a Bayesian approach such as Hamiltonian Monte Carlo could be used (Hoffman and Gelman 2011). Finally, the evidence of spatial model improvement may not be universally true as it is only tested in our specific US corn yield case but cases elsewhere may find stnger or weaker reults. Thus extension to other crops in other regions would be valuable.

In Chapter III, an analysis was presented regarding the effects of alternative ethanol prices, ceteris paribus. In particular the production and input supply costs were held constant nor were there any shifts in commodity demands. However in the real world, ethanol price is related to oil prices which influences the costs of inputs, production, transportation and levels of consumer expenditures. Such considerations would likely increase market penetration costs. Thus, this work could be extended by incorporating the effects of altered energy and associated ethanol prices on input supply and output demand. The essay also ignored possible retrofits allowing existing plants to use alternative feedstocks or lower cost technologies. Future research could include such a possibility.

For Chapter IV, the analysis has several limitations. First, electricity demand and fossil fuel supply are treated as exogenous with supply at a fixed price. Given the large potential market share of renewable electricity price effects would happen and those could affect both the prices of fossil fuel based generation and the demand for electricity. Future extensions could be done by adding endogenous electricity demand as well as supply curves for fossil inputs. Second, for solar the data used were based on utility-scale implementations and more distributed solar could be included. Third, policy affects technology adoption and in this analysis only one national level renewable electricity policy – an Investment Tax Credit - is included in the model whereas regional and other incentives or renewable requirements could be included. Similarly, the electricity price is assumed to be the same country-wide and this could be relaxed including geographically differing prices and markets could be relaxed in future study. Fourth, relaxing the price discount for intermittent sources would require investments in either electricity storage or a more advanced power management system, which are not reflected in this study. Future extensions could be added based on the literature on energy storage utilizing procedures like those in Lazard (2016b).

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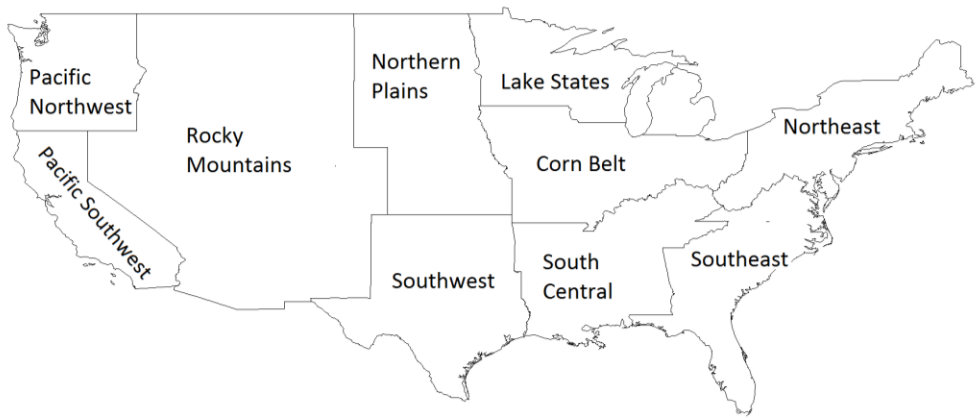
APPENDIX

Appendix 1. Wind and solar supply and cost from ReEDS to FASOM

The FASOM processing regions which divides Continental US into 11 processing regions (Fig. A1) are much larger than spatial resolution of ReEDS, which divides Continental US into 154 regions for solar and 356 regions for wind. We assign each ReEDS region to a FASOM region. As a result, we can generate the supply curve for a FASOM region by horizontally aggregating all the supply curves of those ReEDS regions that are contained in that FASOM region. This is done for both wind and solar.

For each one of the 356 wind regions, ReEDS gives a stepwise supply curve for wind electricity production. Moving along the supply curve from low to high gives us the quantities of wind electricity that could be generated in that ReEDS wind region from cheapest to most expensive. Solar electricity in ReEDS is defined in the similar way.

One key factor that drives up the production cost along the stepwise supply curve within a ReEDS region is that ReEDS categories the resources (namely wind and solar) by their quality and quantifies the capacity for each category. For example, ReEDS divides wind resource into ten categories by wind speed from low to high (the so-called Tech-Resource Group (TRG) from TRG1 to TRG10). As a result, the production cost of wind electricity for a given region goes up as the good-quality resources are exploited and the inferior ones enter production. Solar follows the similar way except it is divided into three categories (PV14, PV20, PV28 by quality from low to high). More explanation is available in the ReEDS documentation by Eurek et al. (2016).



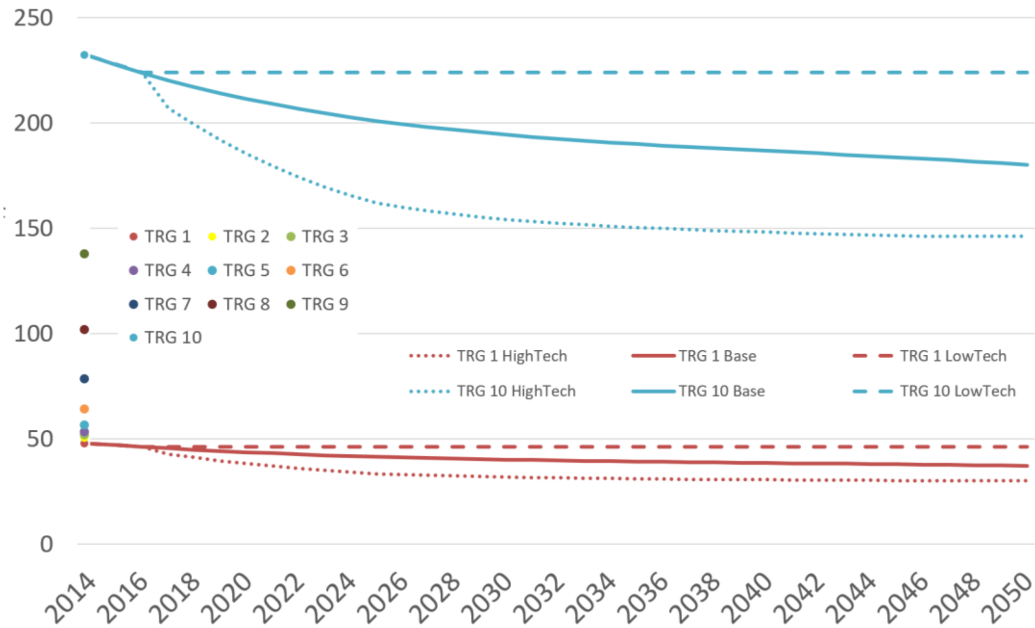
Note: Pacific Nothwest is further divided into east and west side by the Cascade mountain.

Figure A1. FASOM processing regions

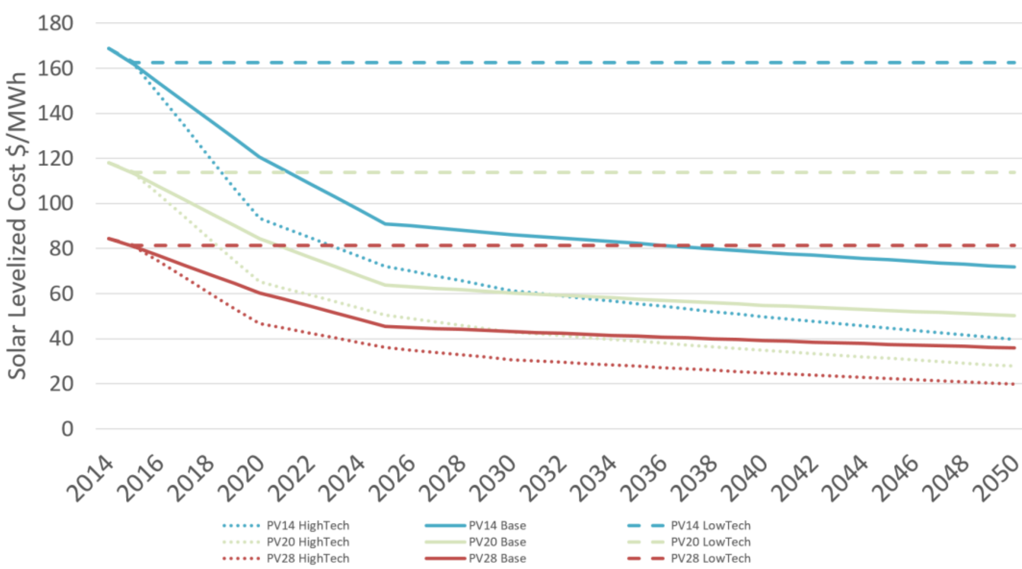
Appendix 2. ATB cost scenarios

The three scenarios in the Annual Technology Baseline 2016 (namely high-cost, mid-cost, and low-cost) are important cost assumption in this study as we mentioned in section 5.1. Detailed assumptions used in the three ATB cost scenarios are available at Hand and Kurup (2016). Here we introduce briefly how the production cost projections for wind and solar vary among different cost scenarios.

According to ATB 2016, resources of different quality classes response differently towards technology progress, which is represented in Fig A2. The solid lines in Fig A2a represents the change of levelized wind electricity production cost over time in baseline scenario due to projected technology progress (only TRG1 and TRG10 are showed due to limited space but the rest classes show similar patterns). Comparing the Baseline and the High-Tech scenarios (as represented by the dotted lines), TRG10 wind has larger reduction in production cost than TRG1 wind. On the contrary, TGR10 wind has larger increase in production cost than TRG1 wind when comparing the baseline and Low-Tech scenarios (as represented by the dashed lines). Interpretation for solar is very similar as showed in Fig. A2b.



(a) Production cost of wind electricity in $/MWh by scenario



(b) Production cost of solar electricity in $/MWh by scenario

Figure A2. Wind and solar electricity cost projection with alternative technology scenarios

Appendix 3. Price discounts for wind and solar with high market penetration

The price discount is a key assumption used in this study to address the intermittency nature of wind/solar electricity. This assumption is based on both empirical data and electricity model results. Empirical price discounts for wind and solar with increasing market share could be calculated as the ratio of the hourly wind/solar-weighted average wholesale electricity price and time-weighted average wholesale price for the entire electricity market. Hirth (2013) showed that the empirical discounts for wind and solar in Germany was decreasing with increasing market share. Specifically, at close-to-zero market share, price discount for solar was greater than one. The reason was that, at this stage the non-dispatchable effect was minor and solar electricity generation is positively correlated to high demand, i.e. for cooling purpose.

Hirth also (2013) estimated through an electricity sector model the discounts for wind electricity ranged from 1.08 with zero market penetration to 0.65 with 30% penetration. Similarly, the he estimated the discount rates for solar ranged from 0.9 with zero MP to 0.55 with 15% penetration. These estimates were used in this study with two changes: (1) discount rates outside the range of estimation (i.e., market share greater than 30% for wind and 15% for solar) was extrapolated with arbitrary small value when market share equaled 100% (0.2 for both wind and solar in this case), and (2) discount rates for solar with small market share was tuned upwards based on empirical data. The final price discounts are illustrated as in Fig. 15.

Appendix 4. Additional scenarios

Since projected renewable electricity market penetration is slow (zero for solar) under the low technology progress scenario, we explore whether policy support can enhance penetration. Consequently, two more scenarios with CO_2 prices are ran and are summarized in Fig. A3. The 2050 total market penetration for renewable electricity even with low technological progress increases to 29% and 42% with the low and high CO_2 prices, respectively. Moreover, wind seems to benefit more from CO_2 pricing, probably because its production cost is already at a low level. On the other hand, solar electricity remains low even with high CO_2 prices. This indicates that solar technology progress/cost reduction is still a prerequisite for widespread commercialization.

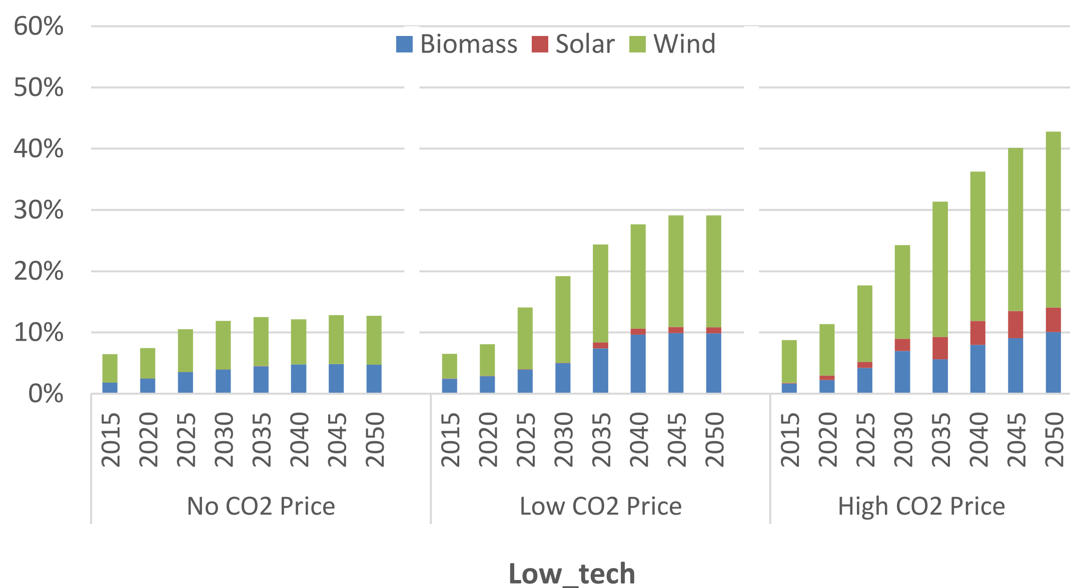


Figure A3. Projected renewables penetration with low technology progress and CO_2 pricing